Christian E. Waugh
Peter Kuppens *Editors*

Affect Dynamics

Springer

Affect Dynamics

Christian E. Waugh • Peter Kuppens
Editors

Affect Dynamics

Springer

Editors
Christian E. Waugh
Wake Forest University
Winston Salem, NC, USA

Peter Kuppens
KU Leuven
Leuven, Belgium

ISBN 978-3-030-82964-3 ISBN 978-3-030-82965-0 (eBook)
https://doi.org/10.1007/978-3-030-82965-0

© The Editor(s) (if applicable) and The Author(s), under exclusive license to Springer Nature Switzerland AG 2021
This work is subject to copyright. All rights are solely and exclusively licensed by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.
The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.
The publisher, the authors, and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, expressed or implied, with respect to the material contained herein or for any errors or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

The notion that affective processes, like emotions and moods, dynamically unfold across time has been around since the beginning of research on affect and emotion. However, it is only in the recent decade or so that advances in affect theory and measurement has allowed researchers to discover the nature of these dynamics as well as the role of these dynamics in development, relationships, personality, and psychopathology. This book features cutting edge research on the theory and measurement of affect dynamics from the leading experts in this blooming field.

This book will differentiate itself from other books on affect dynamics by focusing not only on the fact that they occur, but also on understanding how and why they occur. To understand how they occur, authors will explore affect dynamics at different time-scales. The first time-scale is *Within-episode Affect Dynamics*, in which authors discuss how single emotional episodes may unfold including the duration of affective responses, the dynamics of regulating those affective responses, and how these are instantiated in the brain. The second time-scale explored is *Between-episode Affect Dynamics*, in which authors will discuss how emotions and moods at one point in time may influence subsequent emotions and moods, and the importance of the time-scales on which we assess these dynamics.

Understanding how affect dynamics occur across these different time-scales will lay the foundation for authors to explore why they occur, which will ensure that this book truly advances the field of affect and affect dynamics. This book will open with a call by the editors for researchers to stop treating time like the cause of affect dynamics, but rather to theorize on the dynamic psychological and situational processes that are causing these changes in affect across time. By exploring the causal antecedents of affect dynamics in their chapters, authors will provide novel ideas for generating new theories, models, and measurement of affect and affect dynamics. This call for understanding causal antecedents is particularly apparent in the section on *Between-person Dynamics* in which authors propose that interactions and relationships with others form much of the basis of our affect dynamics.

Integral to understanding affect dynamics is to understand how they are assessed and this book will feature an array of assessment and analytical techniques. Across all the sections, authors discuss how affect dynamics are instantiated across neural, psychological, and behavioral levels of processing and in the *Computational Models of Affect* section, authors provide state-of-the-art analytical techniques for assessing and modeling temporal changes in affective experiences.

It is becoming increasingly clear that to fully understand affective processes, we must understand *that* affect changes across time, *how* these affect dynamics occur, and *the causal antecedents* of these dynamics. This volume will serve as a reference for both seasoned and beginning affective science researchers to explore these important affect dynamics topics.

Winston Salem, NC, USA Christian E. Waugh
Leuven, Belgium Peter Kuppens

Acknowledgments

When we were approached about editing a volume on *Affect Dynamics* back in the Fall of 2019, we knew that it would be a worthwhile endeavor worthy of the amount of time and effort it would take to make it happen. In the Fall of 2019, though, we were still allowed to leave our houses and mingle with our friends in real life. Little did we know that months later the world was going to change and that we were going to edit a volume and authors would be expected to write chapters in the midst of a global pandemic. So, our most heartfelt gratitude goes out to those who made this possible in the most trying times. Thanks go to our families who endured us being locked away in our "home offices" (aka bedrooms) while putting the volume together. Thanks especially go to these authors who, despite having their worlds turned upside down, were able to contribute masterful chapters to this volume. This is a book about time so we offer a final thank you for the timing of this invitation. If it had been offered just 2 or 3 months later, it would not have happened, and that would have been a loss for us, the authors, and for the academic community at large.

Introduction

Abstract Among the many faculties of the mind, affect and emotions are perhaps the most quintessentially dynamical in nature. Meant to alert us of relevant threats and opportunities, our emotions and affective experiences dynamically fluctuate across time and situations. The field of affect dynamics research sets out to understand this temporal nature of affect and how it plays a role in other domains of functioning. With this volume, we are very happy to bring together a collection of contributions that review past research on affect dynamics and on the basis of that discuss how affect dynamics research can move forward into the future. In this first chapter, we first briefly introduce the field of affect dynamics research, discuss the role of time in affect, and introduce the major sections of this book and the chapter featuring in each.

Keywords Affect dynamics · Emotion · Mood · Time · Computational models · Interpersonal

As we and others have used up all the time-themed expressions to start a piece on affect dynamics (It's about time!, Time to get personal, Timing matters, A matter of time, The time is now…), we decided to start this introductory chapter without a playful reference to the concept of time. Oh, who are we kidding—there is no better time than now to conceive a book on the topic of affect dynamics. Affect dynamics research is at a turning point. It can bow on a now rich and diverse research tradition that has pursued crucial questions related to the very nature of emotion and their role in many different domains of life. It has helped to create important theoretical contributions and methodological innovations, and time is taken way more seriously when addressing issues related to emotion than ever before. At the same time, as a field grows, initial enthusiasm matures into reflections about the fundamental theoretical underpinnings and methodological complexities involved in capturing the time dimension of affect. In a way, this book is a reflection of this maturation.

On the one hand, the interested reader will find in this volume an up-to-date overview of much of the research that has taken place over the past couple of decades on various time-dynamic affective phenomena and processes. On the other hand, many if not all chapters also highlight a number of issues the field has been grappling with and provide guidance on how the future of our field can deal with these issues. We will walk you through the individual chapters later in this introduction, but first let us define the field of affect dynamics, and say a few words on the role of time in affect dynamics.

The Field of Affective Dynamics

Among the many faculties of the mind, affect and emotions are perhaps the most quintessentially dynamical in nature. Looking at the history of psychology, many psychological constructs like personality, intelligence, values, preferences, etc. have mostly been conceptualized and/or studied as relatively stable characteristics. Not so for affect and emotion. From the start (be that the start of scientific psychology, or treaties of emotion from early philosophers), it was clear that emotions and our affective experiences are inherently changing, fluctuating phenomena. Emotions are thought to inform us about the way events in the world (or in our mind) relate to what we deem important. This interaction lends emotions a fundamentally dynamic nature, with changes occurring if events change and/or what we consider important changes. In addition, the ability of our mind to foresee, construct, or remember these events means that emotions can be anticipatory or can linger on after events have dissipated. Understanding the resulting dynamical properties and what they tell us about emotions is the focus of the field of affect dynamics research.

As mentioned, emotions have been considered dynamic from the start, and early theories and empirical efforts have taken this into account (although it should also be mentioned that a lot of research has not). Pioneering work is from way before our time, such as the work on intensity profiles and duration of emotional episodes by Frijda and colleagues (e.g., Frijda et al., 1991; Sonnemans & Frijda, 1994) or work on affective chronometry by Davidson (1998).

Building on this work, in previous writing, we have demarcated the study of affective dynamics as "the study of … the trajectories, patterns, and regularities with which emotions, or one or more of their subcomponents (such as experiential, physiological, or behavioral components) fluctuate across time, their underlying processes, and downstream consequences" (p. 71, Kuppens & Verduyn, 2015).

This description is relatively broad, with the intention to both involve short-term fluctuations as one can observe within a single emotional episode and to incorporate longer term patterns that occur between episodes (a distinction we revisit in the structuring of this volume). Also, while not explicitly emphasized in this description, it should also be kept in mind that affect dynamics are not considered to reside in the mind of an individual alone. As emotions typically originate not within but between people (Parkinson, 2019), the field of affect dynamics is concerned both with intra-individual and interindividual processes and phenomena (again something that is reflected in the structuring of this volume).

Although in many ways the study of affect dynamics involves and overlaps with many other areas and questions being pursued in affective science, its common denominator is the explicit recognition that a thorough understanding of the nature, causes, and consequences of emotions entails explicitly taking into account their dynamical nature. The individual contributions of this volume deliver testimony of this viewpoint.

Time Is Not the Cause of Affective Dynamics

When assessing affective dynamics, we typically assess the change of emotional/affective states across time, so it is tempting to think about time as the causal agent of those changes. This thinking is reflected in lay phrases like "time heals all wounds" as well as in articles on affective dynamics that feature causal language like "time increased the arousal of…" and "time-induced stress…" From our perspective, however, time is never a causal agent of affective dynamics. Time does not cause anything by itself. Rather, other causal agents of affective dynamics occur across time and it is only our perception that time is the cause of these changes.

We start not with emotion or even psychology but with the myriad of other disciplines that feature time as a central component of their theories and equations. In physics, Einstein's theory of relativity was one of the first theoretical suggestions that time is not a constant but rather exists relative to one's perspective (Vaccaro, 2018). In modern quantum theories, theorists have suggested that most quantum equations can be written without even referencing time (Rovelli, 2018) and that time is a set of quantum states that co-exist with equal status such that the future is as fixed as the past (Minkowski, 1908). In geology, erosion is the rate at which some part of the surface of the earth is worn down over time; however, it is not caused by time but by physical agents like water and air. In biology, the evolution of a species is reflected in the change in genetic makeup of a species over time, but is not caused by time but by the insertions and deletions of genetic mutations from one generation to the next. Indeed, the theory of punctuated equilibrium suggests that some evolutionary changes occur rapidly between long time periods of little to no change (Gould, 2007). And in anatomy, aging occurs because our body experiences oxidative stress, telomere shortening, mutations, and other damage to body structures over time (Liochev, 2015), and not because of time itself. We perceive erosion, evolution, and aging as being caused by time in part because the quantum states of time can be ordered (due mainly to entropy), and it is this order that leads people to subjectively feel like time and time-linked processes flow in one direction (Vaccaro, 2018).

Returning now to psychology, there are several instances of psychological processes that seem to be caused by time but evidence suggests that they are also caused by other mechanisms that change over time. For example, for working memory, there is a robust finding that people's ability to remember information tends to get worse, or decay, over time (Barouillet & Camos, 2012). However, there is research and theory to suggest that time is not the cause of this working memory decay but rather that it is caused by other processes (attention, memory, perceptual, etc.) that interfere with working memory over time (Lewandowsky & Oberauer, 2009). In affective dynamics, the idea that "time heals all wounds" suggests that time itself is the causal agent in emotional/physiological recovery from a stressful event. Indeed, recovery is typically measured as the change in response to some stressor over time and frequently returns to baseline. However, recovery rates are impacted by mechanisms such as active (Schraub et al., 2013) and passive emotion regulation (Foa & Kozak, 1986), and rumination (Glynn et al., 2002). Indeed, extinction of a conditioned fear stimulus can lead to decreased emotional and physiological reactivity over time; however, it has been shown that this is a form of learning and not just the gradual time-locked decay of fear as evidenced by spontaneous recovery of the initial fear response later (Myers & Davis, 2007). In addition, sometimes affective recovery does not actually return to baseline at all after a perturbation (Lucas, 2005), suggesting that something permanent has changed and that time itself cannot reverse it.

Therefore, when constructing this volume we insisted that the authors not rely on the crutch that time is the causal agent of affective dynamics, but to rather explore the actual causal mechanisms of their affective changes of interest. We strongly believe this resulted in a series of chapters that are quite novel in their exploration of the causal agents of affective dynamics and will most assuredly lead to significant advances in this field for years to come.

This Volume

The structure we have adopted for this volume can be compared to a camera that slowly zooms out from its object of focus to take in more and more of the broader picture and context in which the object is situated. Specifically, we start with a number of chapters that mostly focus on within-episode dynamics. While our emotional life is arguably characterized by a remarkable continuity, nevertheless specific events can trigger what has been termed emotional episodes, which typically have an identified onset and offset. The first couple of chapters address the dynamics that take place within the context of such an episode.

In short, starting with a micro focus on how to demarcate such emotional episodes, Verduyn addresses the duration of emotional episodes. This requires determining what can be considered as the start and ending of an emotional episode, and this chapter discusses research that tackles this important first question.

Next, Everaert et al. propose a predictive mind model to capture how appraisals originate are updated and revised and as such shape the trajectory of the emotional episode between its beginning and ending. In the last chapter of this section, Heller reviews research on the neural basis of the dynamics within emotional episodes, encompassing rise-time, intensity and duration of emotional episodes, and paying explicit attention to the different time-scales on which different emotion components operate.

Whereas the previous section was mostly concerned with what happens within an emotional episode, the next section zooms out a little bit and brings together a number of contributions that mostly focus on between-episode dynamics. The issues discussed in this section are situated on a longer time-scale and consider how emotions and affective experiences vary over longer periods of time.

First, Koval et al. hones in on one of the most basic but intriguing temporal characteristics of affect, namely its autocorrelated, self-predictive, or inert nature. Indeed, due to processes laid out in the chapter, emotions and affect last longer than the presence of the eliciting stimulus and can linger more or less after the initial event is over. This means that affect is autocorrelated, meaning that how one feels can be predicted by how one feels at a previous moment in time, with interesting implications for understanding the nature of emotion and also its role in disorders of emotion and affect. Next, Lazarus et al. take on this perspective of between-episode dynamics and suggest a number of key issues and concerns that have to be taken into account when studying the dynamics of affect on longer time-scales. Hollenstein joins this discussion by warning affect dynamics researchers to not overstate their claims based on data that do not reflect the processes they target on the correct time-scale and context. Finally, Dejonkcheere et al. summarize many of the previous issues under the banner of signal-to-noise ratio in affect dynamics data and offer a number of concrete suggestions on how to increase this, effectively dealing with many of the issues that have been raised in this section.

Where the previous two sections were mostly concerned with the intrapersonal dimension of affect dynamics, the two chapters in the next section take an even broader perspective and zoom out to the interpersonal level. First, Sels et al. provide an overview of interpersonal affect dynamics research and put forward two elements that are key to understanding the temporal patterns with which people emote together, interdependence and perceived partner responsiveness. Against this background, they provide excellent suggestions to move the field of interpersonal affect dynamics research forward. Next, Mobbs et al. approach the topic of affect dynamics from an interpersonal drives perspective, arguing how three fundamental social drives shape and are shaped by affect dynamics and as such are able to pinpoint what constitutes healthy and unhealthy functioning.

One could argue that the final section discusses attempts to bring all elements into unified frameworks in the form of computational models for affect dynamics. Computational models do not just help researchers analyze the complex and large amount of time series data typically encountered in affect dynamics research, but they provide for formalized theories of the mechanisms and processes involved in affect dynamics, make them directly amenable to empirical testing, and allow researchers to pit theories against each other and directly evaluate how they perform in explaining empirical data. As such they are an extremely valuable tool for theory construction, theory evaluation, and for making sense of the often complex data collected in affect dynamics research. First, Loossens, et al. provide a non-exhaustive but broad overview of families of computational models presented in the literature, distinguishing between discrete- and continuous time models, and highlighting the strengths and weaknesses of particular approaches or proposals. This overview is excellent for readers who want to become acquainted with different computational modeling approaches out there, addressing the basics but also not shunning important technical elements. Next, the final two chapters present particular computational modeling approaches developed to grasp dynamics in affect regulation and subjective experience of affect, respectively. Nimat et al. propose a family of computational network models to capture the flexibility and adaptation in context-dependent emotion regulation processes. Next, Kishida et al. propose the Dynamics Affective Core hypothesis in which they draw on dopaminergic reinforcement learning to model how the brain generates moment-to-moment changes in affective consciousness.

Conclusion

The field of affect dynamics is in its adolescence—mature enough to have formal models and theory-driven hypotheses, but young enough that many of these models have either not been fully tested, or struggle with explaining affective phenomena over and above simpler metrics (e.g., Dejonckheere et al., 2019). This volume does not hide that adolescence, but showcases it with a renewed emphasis on the modeling of affect dynamics, the role of time-scales, and the neural underpinnings of affect dynamics, as well as a relatively novel emphasis on understanding that affect dynamics are caused by psychological and environmental mechanisms and not by time itself.

Department of Psychology
Wake Forest University,
Winston Salem, NC, USA
Christian E. Waugh
waughce@wfu.edu

KU Leuven
Leuven, Belgium
Peter Kuppens
peter.kuppens@kuleuven.be

References

Barrouillet, P., & Camos, V. (2012). As time goes by: Temporal constraints in working memory. *Current Directions in Psychological Science, 21*(6), 413–419. https://doi.org/10.1177/0963721412459513

Davidson, R. J. (1998). Affective style and affective disorders: Perspectives from affective neuroscience. *Cognition & Emotion, 12*, 307–330.

Foa, E. B., & Kozak, M. J. (1986). Emotional processing of fear: Exposure to corrective information. *Psychological Bulletin, 99*(1), 20–35. https://doi.org/10.1037/0033-2909.99.1.20

Frijda, N. H., Mesquita, B., Sonnemans, J., & Van Goozen, S. (1991). The duration of affective phenomena or emotions, sentiments and passions. In K. T. Strongman (Ed.), *International review of studies on emotion* (Vol. 1, pp. 187–225). Chichester, England: Wiley.

Glynn, L. M., Christenfeld, N., & Gerin, W. (2002). The role of rumination in recovery from reactivity: Cardiovascular consequences of emotional states. *Psychosomatic Medicine, 64*(5):714–26. https://doi.org/10.1097/01.psy.0000031574.42041.23

Gould, S. J. (2007). *Punctuated equilibrium*. Harvard University Press, MA.

Kuppens, P., & Verduyn, P. (2015). Looking at emotion regulation through the window of emotion dynamics. *Psychological Inquiry, 26*, 72–79.

Lewandowsky, S., & Oberauer, K. (2009). No evidence for temporal decay in working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 35*(6), 1545–1551. https://doi.org/10.1037/a0017010

Liochev, S.I. (2015). Reflections on the theories of aging, of oxidative stress, and of science in general. Is it time to abandon the free radical (oxidative stress) theory of aging? *Antioxidants & Redox Signaling, 23*(3), 187–207.

Lucas, R. E. (2005). Time Does not heal all wounds: A longitudinal study of reaction and adaptation to divorce. *Psychological Science, 16*(12):945–950. https://doi.org/10.1111/j.1467-9280.2005.01642.x

Minkowski, H. (1908). *Space and Time, reprinted in 2012. Space and Time - Minkowski's Papers on Relativity* (trans by F. Lewertoff and V. Petkov). Montreal, QC, Canada: Minkowski Institute.

Myers, K., & Davis, M. (2007) Mechanisms of fear extinction. *Molecular Psychiatry, 12*, 120–150. https://doi.org/10.1038/sj.mp.4001939

Parkinson, B. (2019). *Heart to heart*. Cambridge University Press.

Rovelli, C. (2018). *The order of time*. Riverhead books, New York, NY.

Schraub, E. M., Turgut, S., Clavairoly, V., & Sonntag, K. (2013, October 14). Emotion regulation as a determinant of recovery experiences and well-being: A day-level study. *International Journal of Stress Management*. Advance online publication. doi: 10.1037/a0034483

Sonnemans, J., & Frijda, N. (1994). The structure of subjective emotional intensity. *Cognition and Emotion, 8*, 329350.

Vaccaro, J.A. (2018). The quantum theory of time, the block universe, and human experience. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376*(2123), 1–13.

Contents

Part I Within-Episode Dynamics

Part II Between-Episode Dynamics

Part III Between-Person Dynamics

Part IV Computational Models of Affect

About the Editors

Christian E. Waugh Dr. Christian Waugh is currently an Associate Professor of Psychology at Wake Forest University. He received his PhD in Social Psychology and Cognitive Neuroscience from the University of Michigan where he worked on the role of positive emotions in social cognition and resilience. After receiving his PhD, he did a postdoctoral fellowship at Stanford University where he investigated the neurobiology of stress and the temporal dynamics of emotions in at-risk populations. Currently, Dr. Waugh investigates the contextual utility of positive emotions during stress and the temporal dynamics of emotions. He has expertise in survey, experimental, peripheral, psychophysiological, and neuroimaging methods. He has also received two faculty fellowship awards for being an outstanding teacher-scholar. He has given invited presentations all over the world and his work has been featured in both print and on television. He has learned the most about affect dynamics by watching his four children grow up and have emotions that change all the time.

Peter Kuppens Dr. Peter Kuppens is Professor of Psychology at KU Leuven-University of Leuven in Belgium. He obtained his PhD in Psychology from KU Leuven in 2004 and from 2008 to 2010 has been a Research Fellow at the University of Melbourne. His earlier research concerned the appraisal basis of emotions, focusing on understanding the person- and context-specific nature of emotional experience. This work led him to start studying emotions as inherently time-dynamic phenomena, with an aim to identify the major patterns of affect dynamics, their underlying processes, and their downstream consequences for psychological well-being and psychopathology. In his research, he makes use of insights from affective, clinical, and personality science, relies on both lab-based and ambulatory methods of data collection, and on the application of mathematical modeling tools to make sense of complex time series data. He is a fellow of the Association for Psychological Science and the Society for Personality and Social Psychology. He likes cats but in a cruel twist of fate and to the dismay of his children is allergic to them.

Part I
Within-Episode Dynamics

Chapter 1
Emotion Duration

Philippe Verduyn

Abstract Emotions are processes that unfold over time. This implies that research on dynamic features of emotions is needed to understand how emotions operate. One key dynamic feature is emotion duration. For a long time, no research on emotion duration was conducted. However, during the last three decades, our understanding of emotion duration increased significantly. In the present chapter, I provide an overview of research on emotion duration. First, I define emotion duration and discuss the conceptual complexities surrounding the start and end of an emotional episode. Next, I describe studies that examined how long emotional episodes last. These studies converged on the conclusion that emotion duration is highly variable with episodes lasting for seconds, minutes, hours or even longer. Subsequently, I review research examining the mechanisms underlying emotion duration. These mechanisms include psychological processes that occur at the start of an emotional episode, as the initial appraisal of an emotion-eliciting event and intensity of the emotional response are major determinants of emotion duration. Moreover, emotion duration also depends on psychological processes that unfold during the emotional episode as dynamics in attention, appraisals and regulation strategies prolong or shorten emotional episodes. The chapter ends with directions for future research.

Keywords Emotion duration · Definition · Determinants · Mechanisms · Attention · Appraisals

1.1 Introduction

Emotions are not stable states but are constantly in flux. This implies that research on the dynamic properties of emotions is necessary to understand how they operate. However, for a long time research on emotion dynamics was scarce (Frijda, 2007).

P. Verduyn (✉)
Faculty of Psychology and Neuroscience, Maastricht University, Maastricht, Netherlands
e-mail: philippe.verduyn@maastrichtuniversity.nl

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_1

Researchers studied the processes underlying the onset of an emotional response but paid little attention to how emotions subsequently unfold over time.

This situation changed from the nineties onwards when researchers started to examine emotion dynamics, inspired by the pioneering work of Davidson (Davidson, 1998), Frijda (Frijda et al., 1991) and Scherer (Scherer & Wallbott, 1994), amongst others. This increase in research efforts resulted in a better understanding of the dynamic properties of emotions due to which the research field of emotion dynamics is one of the most enticing research fields within affective science today.

Research on emotion dynamics pertains to the study of the trajectories, patterns, and regularities with which emotions or their components (i.e., the experiential, physiological, and behavioural components) fluctuate across time. Researchers operating in this field do not only describe these temporal changes but also examine underlying processes and downstream consequences of these changes (Kuppens & Verduyn, 2015). To measure emotion trajectories, a wide range of tools are available. Each tool has its own advantages and disadvantages as illustrated by two common methods to measure trajectories of emotional experience: the experience sampling approach and the intensity profile approach.

Experience sampling entails asking participants multiple times per day to report on how they feel (e.g., how sad do you feel right now?) during the period following a particular emotional event (e.g., Villano et al., 2020) or during a random segment of a participant's life (e.g., Brans et al., 2013). A key advantage of this approach is that memory bias is minimal but the resulting data is discrete and short-term changes in emotional experience may go by unnoticed.

The intensity profile approach entails asking participants to draw intensity profiles of their emotional experiences (Sonnemans & Frijda, 1994). The resulting data are continuous but memory bias may influence the collected data when reporting on past emotional experiences (e.g., Verduyn et al., 2009b). To avoid this, one may ask people to draw profiles while experiencing an emotion (e.g., Hutcherson et al., 2005) but this approach cannot be adopted outside the lab.

To describe variability in emotion trajectories, a wide range of features have been proposed and studied (for an overview, see Kuppens & Verduyn, 2015). Among these, one key feature is the duration of emotions. The importance of this particular feature is reflected by the observation that people sharing their emotions do not only often spontaneously describe the nature (e.g., I was *angry* at him) and intensity (e.g., I was *very* angry at him) but also the duration of their emotions (I was very angry at him *all day long*). Moreover, the duration of emotional episodes has major consequences for physical and mental health (Lapate & Heller, 2020).

The aim of this chapter is to provide an overview of research on emotion duration building on previous reviews of literature on this dynamic feature (Van Mechelen et al., 2013; Verduyn et al., 2015). Specifically, I will first define emotion duration. Next, I will review empirical evidence on how long emotions tend to last. Subsequently, I will illustrate that the duration of emotions is not only determined by events that take place at the start of an emotional episode but also by processes that unfold during an emotional episode. Finally, I will end this chapter by providing some suggestions for future research followed by a concluding statement.

1.2 What Is the Definition of Emotion Duration?

Emotion trajectories reflect the continuous level of a particular emotion or emotion component over time. Typically, these trajectories show fluctuations. For example, when people are asked to report their level of anger repeatedly throughout the day, the resulting trajectory is unlikely to be a flat line. A wide range of factors causes these fluctuations to take place including biological rhythms, sleeping patterns or (insufficient) food intake. However, major shifts in emotion trajectories are often due to the occurrence of particular events, which initiate the start of so-called emotional episodes (Kuppens & Verduyn, 2015).

Emotion duration refers to the duration of emotional episodes. Specifically, the duration of an emotional episode refers to the amount of time between the start and end of an emotional episode (Verduyn et al., 2015). The start of an emotional episode corresponds with the occurrence of a particular event which is relevant for one's goals or concerns (Frijda, 2007). This differentiates emotional episodes from moods, which do not have a clear cause or object (Beedie et al., 2005). It should be noted that the emotion eliciting event can be an external event (e.g., seeing a spider) but also an internal event as when imagining, recalling or anticipating events (e.g., thinking of a spider). Moreover, when thinking about external future events, an emotional episode can start before the external event takes place. For example, an emotional episode of anxiety typically does not start when giving a speech but rather when starting to anticipate having to give a speech.

The end of an emotional episode is more difficult to delineate than the onset. Overall, two different conceptualizations can be distinguished. First, the end of an emotional episode can be equated with the first point in time at which emotion intensity reaches zero or, similarly, returns to a baseline level (Verduyn et al., 2009a, 2011, 2012b). An advantage of this conceptualization is that it is relatively straightforward to determine when an emotional episode ends, which allows studying emotion duration empirically in a relatively straightforward manner. A disadvantage, however, is that this conceptualization does not take into account that emotions may be re-elicited after having returned to their baseline level. For example, following an insult an episode of anger may be initiated. This feeling may persist until running into a friend with whom one has a pleasant conversation during which anger is no longer felt. The start of this conversation therefore constitutes the end of the emotional episode of anger. However, once the conversation is over, one may immediately recall the insult and feel angry again. When equating the end of an emotional episode with a first return to baseline, the moment of recalling the insult following the conversation would be conceptualized as the start of a totally new emotional episode, while, in fact, it is directly related to the preceding anger episode.

Second, the end of an emotional episode can be equated with the moment in time at which the episode is "closed" in the sense that the emotion intensity associated with an emotion-eliciting event reaches zero (or baseline) in a permanent manner (Frijda et al., 1991; Frijda, 2007). Closure is reflected by a lack of spontaneous recollections of the emotional event and a lack of emotional reactivity in those rare cases the emotional event would be recollected. This may be accompanied by decreased emotional detail in the autobiographical memory representation of the emotion-eliciting event (Beike & Wirth-Beaumont, 2005). For example, following an insult one may experience anger for several days. This experience of anger may be temporarily interrupted by several periods during which one feels calm but only when an apology is received, the emotional episode may be fully closed.

An advantage of this conceptualization is that it distinguishes temporary relief (i.e., a temporary non-stable return of emotion intensity to zero) from stable emotional recovery (i.e., a stable return of emotion intensity to zero) (Frijda, 2007). However, it is often hard to say when an emotional episode is fully closed and some emotional episodes may never end according to this conceptualization, making it especially hard to study emotion duration at an empirical level.

1.3 How Long Do Emotions Last?

For a long time, it was believed that emotional episodes only last for seconds up to a few minutes at most (Ekman, 1984). This belief was largely based on animal models of emotion (Darwin, 1965) and observations of the duration of emotional expressions in the lab (Ekman & Friesen, 1982). However, animal models and lab data on emotion expression do not represent particularly well how long an emotion can last (Frijda, 2007; Rimé, 2009). Several lines of research indicate that typically emotions last longer than a few seconds or minutes.

First of all, while activation in the behavioral or expressive component of emotional responses may be shorter than activation in the other components of an emotional response, some data is available suggesting that even activation in emotional expression may last longer than just a few minutes (Bylsma et al., 2011). Moreover, while data on physiological recovery observed in the lab is generally consistent with the notion of emotions lasting for a few minutes only (e.g., Fredrickson & Levenson, 1998), data on cardiovascular recovery following stressful events in daily life, reveal significantly longer recovery periods (Pieper & Brosschot, 2005). Furthermore, data on the duration of the conscious emotional experience component of an emotional response show convincingly that these experiences typically do not end within a few minutes only.

Most studies on emotion duration have focused on the duration of emotional experience as obtained through self-report questionnaires. In these studies the end of an emotional episode was either not explicitly defined to the participants (e.g., Scherer & Wallbott, 1994) or defined to occur when emotion intensity returned to zero or a baseline level for the first time (e.g., Verduyn et al., 2009a), which corresponds to the first conceptualization mentioned above. Research explicitly using the second conceptualization (permanent return to baseline) is rare, but non-surprisingly, participants reported longer emotions when the end of an emotional episode was defined to them to correspond to a permanent return to baseline, rather than a first return (Verduyn & Lavrijsen, 2015).

Critically, regardless of the duration definition employed, it was found that emotional experiences can last for seconds but usually these experiences last longer. Specifically, the duration of emotional experiences was found to be highly variable with durations ranging from a few seconds to several hours, or even longer. Moreover, in each study on the duration of emotional experiences in daily life, duration averages clearly exceeded a few minutes (Frijda et al., 1991; Gilboa & Revelle, 1994; Scherer & Wallbott, 1994; Verduyn et al., 2009a, 2011, 2012a, b, 2013).

While most people tend to experience emotions that often last longer than only a few minutes, certain people tend to experience longer emotions than others do. At the level of socio-demographic factors, evidence is available that older adults experience longer positive emotions and shorter negative emotions than younger adults (Charles et al., 2016). Moreover, negative emotions were found to last longer in collectivistic and poorer countries than in individualistic and rich countries, respectively (Verduyn et al., 2013). At the level of personality dimensions, extraverts were found to tend to experience longer positive emotions than their introvert counterparts (Verduyn & Brans, 2012), while neurotics experience longer negative emotions than their emotionally stable counterparts (Schuyler et al., 2012; Verduyn & Brans, 2012). At the level of indicators of mental health, resilient people were found to show accelerated recovery from stressful encounters (Tugade & Fredrickson, 2004). This should not come as a surprise as resilience refers to the ability to cope effectively and adapt in the face of loss, hardship, or adversity (Block & Kremen, 1996). Moreover, consistent with diagnostic criteria, depressed individuals were found to be unable to sustain activity in neural circuits underlying positive affect (Heller et al., 2009) while showing longer activation in neural regions associated with negative emotions (Siegle et al., 2001, 2002).

It is not only the case that some people tend to experience longer emotions than others do but also some types of emotions tend to last longer than other types of emotions. Several studies have been conducted to compare the duration of different emotions and the results of these studies largely overlap (Gilboa & Revelle, 1994; Scherer & Wallbott, 1994; Verduyn et al., 2009a, 2011, 2012a, b). The largest set of emotions was studied by Verduyn and Lavrijsen (2015). They found that out of 27 emotions, sadness lasted the longest, whereas shame, surprise, fear, disgust, boredom, being touched, irritation, and relief were the shortest emotions. In some cases, the size of differences was quite remarkable with sadness lasting on average 240 times longer than the shortest emotions under study but in most cases duration differences were much smaller.

In sum, emotions can last for only a few seconds but usually last for minutes, hours or even longer. However, why do some people tend to experience longer emotions than others do? Why do certain types of emotions tend to last longer than other types of emotions? Moreover, what causes differences in duration between two episodes of the same type of emotion, experienced by the same person? These questions bring us to the next section where I discuss determinants of emotion duration.

1.4 What Determines the Duration of an Emotion?

1.4.1 What Happens at the Start Impacts How Long It Takes to Get to the End

By definition, an emotional episode is initiated by the occurrence of an internal or external event. The perceived nature of this event has a major impact on the duration of the ensuing emotional response. In several studies, it was found that the perceived importance of the emotion-eliciting event partially explains duration variability *within emotions*. Specifically, events of higher perceived importance are associated with longer emotional episodes (Verduyn et al., 2009b, 2011). Moreover, compared to short types of emotions such as disgust, relatively long lasting emotions such as sadness are caused by events that are higher in importance. As such, perceived event importance also partially explains duration differences *between emotions* (Verduyn & Lavrijsen, 2015).

Events may be perceived as important because they are especially congruent (in case of positive emotions) or incongruent (in case of negative emotions) with one's goals, norms, values or self-ideals (Frijda, 2007). In the context of negative emotions, it has been shown that the number of perceived mismatches between an event and one's desires predicts the duration of negative emotional experiences and this mismatch-duration mechanism was found to largely hold universally (Verduyn et al., 2013). More recently, it has been shown that the degree to which an event matches one's expectations also impacts the ensuing emotional trajectory (Villano et al., 2020).

However, the duration of an emotional response is not only a function of the (initial) appraisal of an emotional event but also of the initial intensity of an emotional episode. This is the case even when controlling for the perceived importance of an emotional event, which suggests that the role of intensity in predicting duration cannot be fully explained by event importance (Verduyn et al., 2009a, 2011, 2013). When intensity is high at the start of an emotional episode, it takes longer for emotional experience to return to its baseline level. Critically, however, this does not imply that emotional episodes are always, or even typically, characterized by a high intensity peak at the start followed by a gradual return to baseline (Heylen et al., 2015, 2016).

In research using an intensity profile approach to measure trajectories of emotional experience, it was found that such trajectories can take a wide variety of shapes (Sonnemans & Frijda, 1994). Moreover, these intensity trajectories were found to differ primarily in explosiveness, accumulation, and reactivation (Verduyn et al., 2009b, 2012a). Intensity profiles can have (a) a low or high level of initial intensity, reflecting differences in explosiveness, (b) a peak intensity level situated at the start or end of the episode, reflecting differences in accumulation, and (c) a single or multiple intensity peaks, reflecting differences in reactivation. The distinct nature of these dynamic features is corroborated by fMRI studies on the neural correlates of explosiveness and accumulation showing distinctive neural correlates for both features (Résibois et al., 2017, 2018b).

In sum, the degree of mismatch between the event and one's desires as well as the initial intensity of an emotional response impact the duration of an emotional episode. Moreover, the recovery process is not always a linear process characterized by a gradual, uninterrupted return to baseline. Regardless, the emotion-eliciting event sets the stage for the subsequent processes that will unfold over time and that impact the duration of the emotional response, which I turn to in the next section.

1.4.2 Time Itself Does Not Heal All Wounds; What Happens Over Time Matters

A common expression is that time heals all wounds. While this expression may seem correct at the surface level, it raises several questions. For example, is it true that eventually all emotions end? Do feelings of sadness following a major emotional event such as the loss of a child ever return to their baseline level in a stable manner (see second conceptualization of the end of an emotional episode above). Perhaps even more critically, what does it mean to say that time heals all wounds. Does the passage of time automatically result in an emotion running out of steam, like a car having no fuel left to keep driving? While metaphors like this might be intuitively appealing, the construct of time in and off itself does not explain changes in emotions over time. Instead, emotion dynamics are a function of temporal changes in mechanisms that drive emotional responding. In the next paragraph, I discuss two processes that can change with the passage of time and impact the duration of emotional episodes. This is not to say that there are no other dynamic processes that may impact the duration of emotional episodes but these two processes have received substantial empirical evidence.

1.4.2.1 The Role of Attention

An emotion-eliciting event continues to affect the unfolding of an emotional episode during the period following emotion elicitation. In a diary study, Verduyn and colleagues (Verduyn et al., 2009a) asked participants to recall the duration of their emotional episodes experienced earlier that day. For each 15-min interval of the emotional episode, they also asked participants to indicate whether the emotion-eliciting stimulus was physically present or absent. For example, when having an argument, the emotion-eliciting stimulus (i.e., another person) may be present during the first 15 min, leave the room for the next 15 min (possibly slamming the door on the way out), and return back (or not) in the next 15 min. It was found that the physical presence or reappearances of an emotion-eliciting event make it less likely that an emotional episode ends.

In a second, similar study (Verduyn et al., 2009a), the authors examined whether the mental presence of the eliciting stimulus (thinking about the emotion-eliciting event) similarly impacts the duration of an emotional episode. They found this to be the case with the mental presence or mental reappearances of the emotion-eliciting event prolonging emotional episodes. Interestingly, follow-up research revealed that physical and mental reappearances may prolong emotional experiences by causing reactivations (new peaks) within an emotional episode (Verduyn et al., 2012a).

Combined, these results suggest that one key mechanism, which varies over time and influences the duration of emotional responses, is attention. The physical presence of an emotion-eliciting stimulus likely prevents one from diverting attention elsewhere. Similarly, when the eliciting stimulus is mentally present, attention is by definition focused on that particular stimulus. Attention may also explain the connection between (initial) emotion intensity and emotion duration with fMRI research revealing a relationship between intensity and longer duration of activation in regions along the cortical midline associated with self-referent processing (Waugh et al., 2010). Similarly, from a functional perspective on emotions (Keltner & Gross, 1999) one may argue that important events that are especially congruent or incongruent with one's desires require one's attention for a longer time, identifying a possible mechanism explaining the relationship between perceived event importance and emotion duration.

The claim that attention is a major determinant of the duration of emotional responses is consistent with research on emotion regulation. Specifically, it has been shown that distraction (i.e., directing attention away from an emotion-eliciting event) generally reduces the intensity of negative emotions (Fennell et al., 1987; Joormann & Siemer, 2004) while rumination (i.e., excessively focusing attention on the causes and consequences of an emotion-eliciting event) has the opposite effect (Nolen-Hoeksema & Morrow, 1993). Attention has also been shown to explain why long lasting emotions such as sadness tend to last longer than other types of emotions, as long lasting emotions tend to be associated with relatively high levels of rumination (Verduyn & Lavrijsen, 2015). Similarly, neurotics may tend to experience long negative emotions, due to their tendency to ruminate over negative experiences (Nolan et al., 1998).

In some recent work, the relationship between attention and emotion duration was examined even more directly. Freund and Keil (2013) proposed the attention-focus hypothesis according to which the duration of an emotional response to events is crucially determined by the amount of attention they receive. In a first study, they instructed participants to focus attention on an event that recently caused them to experience a positive emotion (having won a chess game) or to focus their attention elsewhere. In a second study, they used a similar experimental design but this time in the context of negative emotions. In both studies, they found that distracting attention away from the emotion-eliciting event leads to a shorter duration of an emotional experience. Consistently, Kaneko et al. (2018) conducted a cross-sectional study and found a positive relationship between attention and the duration of both negative and positive emotions.

A wide variety of factors may influence people's attention during an emotional episode. These include the occurrence of novel events that automatically redirect people's focus elsewhere as well as people's own conscious attempts to direct their focus. One particular interesting emotion regulation strategy that may cause people to sustain their attention on the emotional event is social sharing. Research on social sharing showed that people share their emotions with others in the large majority of cases (Rimé et al., 1998). In case of positive emotions, it has been shown that sharing is associated with longer episodes of positive emotion and more time spent thinking about the positive event (Hovasapian & Levine, 2018). However, in case of negative emotions results on the impact of social sharing on episode duration are less clear-cut (Brans et al., 2014; Pe et al., 2013; Rimé, 2009).

In sum, previous research indicates that focusing attention on an emotion-eliciting event is generally positively associated with the duration of emotional experience while distraction shortens emotional episodes. However, three critical remarks are needed to nuance this conclusion. First, not all types of distraction shorten emotional episodes. In contrast to positive distracting thoughts, negative distracting thoughts do not shorten the duration of negative emotions. Similarly, in contrast to negative distracting thoughts, positive distracting thoughts do not shorten the duration of positive emotions (Verduyn et al., 2011). Second, the effects of distraction may be short-lived. Distraction may shut down an emotional episode temporarily as reflected by a first return of emotion intensity to a baseline level (first conceptualization of the end of an emotional episode mentioned above). However, this return might reflect a state of temporary relief rather than stable emotional recovery (second conceptualization of the end of an emotional episode mentioned above) (Kross & Ayduk, 2008). Third, while focusing attention on an emotional episode may generally prolong emotional episodes, it may also shorten emotional episodes as explained in the next section.

1.4.2.2 The Role of Appraisal Dynamics

To examine whether all types of mental reappearances prolong the duration of emotional experiences, Verduyn and colleagues conducted a follow-up study (Verduyn et al., 2011). Similarly to their original study (Verduyn et al., 2009a), they used a diary design asking participants to recollect the emotions they experienced earlier that day. However, rather than asking participants to indicate for several time-segments of the emotional episode whether the emotion-eliciting stimulus was mentally present or not, they asked participants to specify the valence of their thoughts about the emotion-eliciting stimulus. They found that during negative emotional episodes, participants reported most often negative thoughts about the emotion-eliciting event and these thoughts (e.g., “he really enjoys hurting me”) prolonged negative emotional episodes. Critically, however, when people had positive thoughts about the negative emotion-eliciting event (e.g., “he probably did not mean it that way”), this increased the probability that a negative emotional episode would end at that moment in time. In case of positive emotions a similar pattern was found with positive (negative) thoughts about the emotion-eliciting event prolonging (shortening) the emotional episode.

The finding that during negative (positive) emotional episodes people tend to have negative (positive) thoughts about the emotion-eliciting event may explain why mental reappearances of this event (or focusing attention on this event) were overall found to have a prolonging effect on the duration of emotional experience (Verduyn et al., 2009a). Moreover, the finding that thoughts about the emotion-eliciting event prolong emotional experiences when they share valence, is consistent with research on social sharing of positive emotions showing that the association between sharing and emotion duration was greatest when sharing partners were perceived as highlighting the importance and remarkability of the event, "keeping the magic alive" (Hovasapian & Levine, 2018).

The finding that positive thoughts shorten the duration of negative emotions is consistent with research on positive reappraisal (i.e., reappraising a negative event in a more positive manner). In a wide range of studies, this emotion regulation strategy has been shown to be highly effective at downregulating negative emotional responses (Gross, 1998a, b; Ray et al., 2008), and stimulating emotional recovery over time (Mehta et al., 2020). However, research on contextualized emotion regulation revealed important boundary conditions of the generally adaptive effects of reappraisal (Aldao, 2013).

For example, when people experience intense negative emotions, they are unlikely to engage in reappraisal (Sheppes & Gross, 2011; Sheppes et al., 2011) and reappraisal is ineffective in downregulating intense negative emotions (Raio et al., 2013; Shafir et al., 2015). Similarly, it has been found that people are unlikely to reappraise their emotional experiences at the start of an emotional episode (Kalokerinos et al., 2017), and may respond negatively to sharing partners stimulating cognitive reappraisal at the start of a sharing episode (Rimé, 2009). It should be noted, however, that this is not always dysfunctional as preliminary termination of an emotional episode may interfere with the functional nature of emotions stimulating responsiveness to important changes in one's environment (Keltner & Gross, 1999).

Positive reappraisal may not always come naturally, as when a person experiencing a negative emotion does not manage to see any positive aspect to a negative experience. One strategy that may help in this regard is self-distancing. When people think about an emotional experience, they may do so from a self-immersed perspective in which self-relevant events and emotions are (re-)experienced in a first-person perspective through their own eyes (Nigro & Neisser, 1983). Alternatively, one may adopt a self-distanced perspective in which individuals focus on their experiences from the perspective of an observer or "fly on the wall" (Libby & Eibach, 2002; McIsaac & Eich, 2004).

Verduyn and colleagues examined whether these two perspectives have differential effects on the duration of emotional experience (Verduyn et al., 2012b). Participants were asked to recollect positive and negative emotions experienced earlier during the day, and repeatedly indicated which perspectives they adopted when thinking about the emotion-eliciting event during the emotional episode. People most often adopted a self-immersed perspective but when they managed to think about the emotional event using a self-distanced perspective, the emotional episode was more likely to end. Follow-up research revealed that self-distancing prevents negative emotions to accumulate (Résibois et al., 2018b), and this is especially so in people suffering from high levels of depressive symptoms (Résibois et al., 2018a).

One mechanism through which self-distancing may accelerate emotional recovery is by stimulating positive reappraisal (Kross & Ayduk, 2008).

In sum, while the initial appraisal of an emotional event determines the initial intensity of an emotional response, the appraisal process continues throughout the emotional episode. When the appraisal configuration remains largely stable, the emotion is unlikely to end, unless alternative events capture one's attention leading to a (temporary) termination of the emotional episode. Reappraisal may not always be easy, especially when emotion intensity is high. However, trying to adopt a self-distanced perspective or sharing one's emotional experience with a partner who stimulates reappraisal at the right moment in time, may result in a more positive take on a negative event. These reappraisal processes may shut down the negative emotional episode. Interestingly, the same holds for positive emotions as reappraising a positive event in a negative manner shortens the duration of positive emotional experiences as well.

1.5 Directions for Future Research

Empirical research on emotion duration has demonstrated that emotional episodes can last for seconds, minutes, hours or even longer. Moreover, first insights on the determinants and processes underlying emotion duration have been obtained. However, more work is needed to increase our understanding of the duration of emotions.

First, most research on emotion duration conceptualized the end of an emotional episode as the first return to baseline. While this choice makes emotion duration especially amendable to empirical research, it does not allow concluding whether a particular determinant of emotion duration stimulates only temporary relief or results in stable emotional recovery. For example, distraction and reappraisal processes have both been found to shorten the duration of emotional episodes but while the former may only lead to a state of temporary relief, the latter may be more effective at fully closing an emotional episode (Kross & Ayduk, 2008). Future research is necessary to better disentangle temporary relief from stable emotional recovery.

Second, most research on emotion duration is correlational. As such, it is often not clear whether processes such as attention, perspective taking or reappraisal shut down an emotional episode, or whether the approaching end of an emotional episode (stimulated by other processes) allows one to refocus attention, adopt a self-distanced perspective or reappraise an emotional event. Emotion generation and regulation mutually influence each other over time (Gross, 2015) and more research is necessary to chart and disentangle these effects.

Third, in research on emotion duration, regulation strategies are typically examined in isolation. However, it is increasingly becoming clear that people often use a variety of strategies to regulate their emotions (Brans et al., 2013; Brans & Verduyn, 2014). Some strategies may only impact emotion duration when the strategy is used at the right time (Kalokerinos et al., 2017) or when preceded or followed by other regulation strategies (Peuters et al., 2019).

Fourth, in this chapter I described processes underlying emotion duration at a psychological level. However, ultimately, these processes are mediated at the neural level. First insights into the neural mechanisms underlying emotion duration have been obtained (Heller & Casey, 2016; Verduyn et al., 2015; Waugh et al., 2015). Interestingly, research on the neural basis of emotion dynamics increasingly combines neuroimaging tools with experience sampling methods to overcome the limitations associated with measuring emotion duration in the lab (Heller et al., 2015; Provenzano et al., 2018). Studies like these are highly valuable and will deepen our understanding of the duration of emotions.

Finally, more research is necessary on the duration of the behavioral and physiological component of emotional responses, as well as how these components interact with emotional experience. Due to practical limitations, it was for a long time not possible to properly measure dynamics in all emotion components simultaneously as they unfold in daily life but breakthroughs in affective sensing and computing may spur new exciting insights on emotion duration in the near future.

1.6 Concluding Statement

Kuppens and Verduyn (Kuppens & Verduyn, 2017) formulated four fundamental principles underlying emotion dynamics: the principles of contingency, inertia, regulation, and interaction. These principles also relate to the processes underlying the specific dynamic feature discussed in the present chapter: emotion duration.

According to the principle of contingency, emotions consist of responses to things extrinsic to them. In this chapter, I illustrated how emotional episode arise in response to external and internal events, and how these events, as well as possible other (distracting) events, continue to impact the emotion as it unfolds over time, ultimately influencing the duration of the emotional episode.

According to the principle of inertia, emotions display an intrinsic resistance to change causing them to carry over from one moment to the next. In this chapter, I illustrated that emotional episodes tend to be characterized by valence-congruent thoughts that prolong emotional episodes, consistent with research on emotion-congruent processing (Lerner & Keltner, 2001) showing that the way we feel influences the way we perceive the world, which in turn, feeds back into the way we feel.

According to the principle of regulation, emotions are continuously regulated to maximize fit with a desired state, which may change as the emotion unfolds. In this chapter, I illustrated how emotion regulation strategies as distraction, positive reappraisal, self-distancing and social sharing can be harnessed to shorten the duration of negative emotional episodes by providing counterweight to the forces of emotional inertia.

Finally, according to the principle of interaction, emotions and emotion components continuously interact over time. In this chapter, I discussed research on the interaction between cognitions and the duration of emotional experience but more research applying the principle of interaction to research on emotion duration is necessary.

References

Aldao, A. (2013). The future of emotion regulation research: Capturing context. *Perspectives on Psychological Science, 8*(2), 155–172. https://doi.org/10.1177/1745691612459518

Beedie, C. J., Terry, P. C., & Lane, A. M. (2005). Distinctions between emotion and mood. *Cognition and Emotion, 19*(6), 847–878. https://doi.org/10.1080/02699930541000057

Beike, D. R., & Wirth-Beaumont, E. T. (2005). Psychological closure as a memory phenomenon. *Memory, 13*(6), 574–593. https://doi.org/10.1080/09658210444000241

Block, J., & Kremen, A. M. (1996). IQ and ego-resiliency: Conceptual and empirical connections and separateness. *Journal of Personality and Social Psychology, 70*(2), 349–361. https://doi.org/10.1037/0022-3514.70.2.349

Brans, K., Koval, P., Verduyn, P., Lim, Y. L., & Kuppens, P. (2013). The regulation of negative and positive affect in daily life. *Emotion, 13*(5), 926–939. https://doi.org/10.1037/a0032400

Brans, K., Van Mechelen, I., Rimé, B., & Verduyn, P. (2014). To share, or not to share? Examining the emotional consequences of social sharing in the case of anger and sadness. *Emotion, 14*(6), 1062–1071. https://doi.org/10.1037/a0037604

Brans, K., & Verduyn, P. (2014). Intensity and duration of negative emotions: Comparing the role of appraisals and regulation strategies. *PLoS One, 9*(3). https://doi.org/10.1371/journal.pone.0092410

Bylsma, L. M., Croon, M. A., Vingerhoets, A. J. J. M., & Rottenberg, J. (2011). When and for whom does crying improve mood? A daily diary study of 1004 crying episodes. *Journal of Research in Personality, 45*(4), 385–392. https://doi.org/10.1016/j.jrp.2011.04.007

Charles, S. T., Mogle, J., Urban, E. J., & Almeida, D. M. (2016). Daily events are important for age differences in mean and duration for negative affect but not positive affect. *Psychology and Aging, 31*(7), 661–671. https://doi.org/10.1037/pag0000118

Darwin, C. (1965). *The expression of the emotions in man and animals*. University of Chicago Press.

Davidson, R. J. (1998). Affective style and affective disorders: Perspectives from affective neuroscience. *Cognition and Emotion, 12*(3), 307–330.

Ekman, P. (1984). Expression and the nature of emotion. In K. Scherer & P. Ekman (Eds.), *Approaches to emotion* (pp. 319–344). Lawrence Erlbaum Associates.

Ekman, P., & Friesen, W. V. (1982). Felt, false, and miserable smiles. *Journal of Nonverbal Behavior, 6*(4), 238–252.

Fennell, M. J., Teasdale, J. D., Jones, S., & Damlé, A. (1987). Distraction in neurotic and endogenous depression: An investigation of negative thinking in major depressive disorder. *Psychological Medicine, 17*(41), 441–452.

Fredrickson, B. L., & Levenson, R. W. (1998). Positive emotions speed recovery from the cardiovascular sequelae of negative emotions. *Cognition and Emotion, 12*(2), 191–220. https://doi.org/10.1080/026999398379718

Freund, A. M., & Keil, A. (2013). Out of mind, out of heart: Attention affects duration of emotional experience. *Cognition and Emotion, 27*(3), 549–557. https://doi.org/10.1080/02699931.2012.725574

Frijda, N. H. (2007). *The laws of emotion*. Lawrence Erlbaum Associates Publishers.

Frijda, N. H., Mesquita, B., Sonnemans, J., & Van Goozen, S. (1991). The duration of affective phenomena or emotions, sentiments and passions. In K. T. Strongman (Ed.), *International review of studies on emotion* (pp. 187–225). Wiley.

Gilboa, E., & Revelle, W. (1994). Personality and the structure of affective responses. In S. Van Goozen, N. E. Van De Poll, & J. A. Sargent (Eds.), *Essays on current issues in the field of emotion theory* (pp. 134–159). Erlbaum.

Gross, J. J. (1998a). Antecedent- and response-focused emotion regulation: Divergent consequences for experience, expression, and physiology. *Journal of Personality and Social Psychology, 74*(1), 224–237. https://doi.org/10.1037//0022-3514.74.1.224

Gross, J. J. (1998b). The emerging field of emotion regulation: An integrative review. *Review of General Psychology, 2*(3), 271–299. https://doi.org/10.1037/1089-2680.2.3.271

Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological Inquiry, 26*(1), 1–26. https://doi.org/10.1080/1047840X.2014.940781

Heller, A. S., & Casey, B. J. (2016). The neurodynamics of emotion: Delineating typical and atypical emotional processes during adolescence. *Developmental Science, 19*(1), 3–18. https://doi.org/10.1111/desc.12373

Heller, A. S., Fox, A. S., Wing, E. K., McQuisition, K. M., Vack, N. J., & Davidson, R. J. (2015). The neurodynamics of affect in the laboratory predicts persistence of real-world emotional responses. *Journal of Neuroscience, 35*(29), 10503–10509. https://doi.org/10.1523/JNEUROSCI.0569-15.2015

Heller, A. S., Johnstone, T., Shackman, A. J., Light, S. N., Peterson, M. J., Kolden, G. G., et al. (2009). Reduced capacity to sustain positive emotion in major depression reflects diminished maintenance of fronto-striatal brain activation. *Proceedings of the National Academy of Sciences, 106*(52), 22445–22450. https://doi.org/10.1073/pnas.0910651106

Heylen, J., Van Mechelen, I., Verduyn, P., & Ceulemans, E. (2016). KSC-N: Clustering of hierarchical time profile data. *Psychometrika, 81*(2), 411–433. https://doi.org/10.1007/s11336-014-9433-x

Heylen, J., Verduyn, P., Van Mechelen, I., & Ceulemans, E. (2015). Variability in anger intensity profiles: Structure and predictive basis. *Cognition and Emotion, 29*(1), 168–177. https://doi.org/10.1080/02699931.2014.896783

Hovasapian, A., & Levine, L. J. (2018). Keeping the magic alive: Social sharing of positive life experiences sustains happiness. *Cognition and Emotion, 32*(8), 1559–1570. https://doi.org/10.1080/02699931.2017.1422697

Hutcherson, C. A., Goldin, P. R., Ochsner, K. N., Gabrieli, J. D., Feldman Barrett, L., & Gross, J. J. (2005). Attention and emotion: Does rating emotion alter neural responses to amusing and sad films? *NeuroImage, 27*(3), 656–668. https://doi.org/10.1016/j.neuroimage.2005.04.028

Joormann, J., & Siemer, M. (2004). Memory accessibility, mood regulation, and dysphoria: Difficulties in repairing sad mood with happy memories? *Journal of Abnormal Psychology, 113*(2), 179–188. https://doi.org/10.1037/0021-843X.113.2.179

Kalokerinos, E. K., Résibois, M., Verduyn, P., & Kuppens, P. (2017). The temporal deployment of emotion regulation strategies during negative emotional episodes. *Emotion, 17*(3), 450–458. https://doi.org/10.1037/emo0000248

Kaneko, M., Ozaki, Y., & Horike, K. (2018). Curiosity about a positive or negative event prolongs the duration of emotional experience. *Cognition and Emotion, 32*(3), 600–607. https://doi.org/10.1080/02699931.2017.1324766

Keltner, D., & Gross, J. J. (1999). Functional accounts of emotions. *Cognition and Emotion, 13*(5), 467–480. https://doi.org/10.1080/026999399379140

Kross, E., & Ayduk, O. (2008). Facilitating adaptive emotional analysis: Distinguishing distanced-analysis of depressive experiences from immersed-analysis and distraction. *Personality and Social Psychology Bulletin, 34*(7), 924–938. https://doi.org/10.1177/0146167208315938

Kuppens, P., & Verduyn, P. (2015). Looking at emotion regulation through the window of emotion dynamics. *Psychological Inquiry, 26*, 72–79.

Kuppens, P., & Verduyn, P. (2017). Emotion dynamics. *Current Opinion in Psychology, 17*, 22–26. https://doi.org/10.1016/j.copsyc.2017.06.004

Lapate, R. C., & Heller, A. S. (2020). Context matters for affective chronometry. *Nature Human Behaviour*. https://doi.org/10.1038/s41562-020-0860-7

Lerner, J. S., & Keltner, D. (2001). Fear, anger, and risk. *Journal of Personality and Social Psychology, 81*(1), 146–159. https://doi.org/10.1037/0022-3514.81.1.146

Libby, L. K., & Eibach, R. P. (2002). Looking back in time: Self-concept change affects visual perspective in autobiographical memory. *Journal of Personality and Social Psychology, 82*(2), 167–179. https://doi.org/10.1037/0022-3514.82.2.167

McIsaac, H. K., & Eich, E. (2004). Vantage point in traumatic memory. *Psychological Science, 15*(4), 248–253. https://doi.org/10.1111/j.0956-7976.2004.00660.x

Mehta, A., Formanowicz, M., Uusberg, A., Uusberg, H., Gross, J. J., & Suri, G. (2020). The regulation of recurrent negative emotion in the aftermath of a lost election. *Cognition and Emotion, 34*(4), 848–857. https://doi.org/10.1080/02699931.2019.1682970

Nigro, G., & Neisser, U. (1983). Point of view in personal memories. *Cognitive Psychology, 15*(4), 467–482. https://doi.org/10.1016/0010-0285(83)90016-6

Nolan, S. A., Roberts, J. E., & Gotlib, I. H. (1998). Neuroticism and ruminative response style as predictors of change in depressive symptomatology. *Cognitive Therapy and Research, 22*(5), 445–455. https://doi.org/10.1023/A:1018769531641

Nolen-Hoeksema, S., & Morrow, J. (1993). Effects of rumination and distraction on naturally occurring depressed mood. *Cognition and Emotion, 7*(6), 561–570. https://doi.org/10.1080/02699939308409206

Pe, M., Frederickx, S., Verduyn, P., De Laet, I., Brans, K., Hofmans, J., et al. (2013). The relationship between arousal and the remembered duration of positive events. *Applied Cognitive Psychology, 27*(4), 493–496. https://doi.org/10.1002/acp.2926

Peuters, C., Kalokerinos, E. K., Pe, M. L., & Kuppens, P. (2019). Sequential effects of reappraisal and rumination on anger during recall of an anger-provoking event. *PLoS One, 14*(1), 1–16. https://doi.org/10.1371/journal.pone.0209029

Pieper, S., & Brosschot, J. F. (2005). Prolonged stress-related cardiovascular activation: Is there any? *Annals of Behavioral Medicine, 30*(2), 91–103. https://doi.org/10.1207/s15324796abm3002_1

Provenzano, J., Bastiaansen, J. A., Verduyn, P., Oldehinkel, A. J., Fossati, P., & Kuppens, P. (2018). Different aspects of the neural response to socio-emotional events are related to instability and inertia of emotional experience in daily life: An fMRI-ESM study. *Frontiers in Human Neuroscience, 12*, 1–10. https://doi.org/10.3389/fnhum.2018.00501

Raio, C. M., Orederu, T. A., Palazzolo, L., Shurick, A. A., & Phelps, E. A. (2013). Cognitive emotion regulation fails the stress test. *Proceedings of the National Academy of Sciences, 110*(37), 15139–15144. https://doi.org/10.1073/pnas.1305706110

Ray, R. D., Wilhelm, F. H., & Gross, J. J. (2008). All in the mind's eye? Anger rumination and reappraisal. *Journal of Personality and Social Psychology, 94*(1), 133–145. https://doi.org/10.1037/0022-3514.94.1.133

Résibois, M., Kuppens, P., Van Mechelen, I., Fossati, P., & Verduyn, P. (2018a). Depression severity moderates the relation between self-distancing and features of emotion unfolding. *Personality and Individual Differences, 123*, 119–124. https://doi.org/10.1016/j.paid.2017.11.018

Résibois, M., Rotgé, J. Y., Delaveau, P., Kuppens, P., Van Mechelen, I., Fossati, P., & Verduyn, P. (2018b). The impact of self-distancing on emotion explosiveness and accumulation: An fMRI study. *PLoS One, 13*(11), 1–19. https://doi.org/10.1371/journal.pone.0206889

Résibois, M., Verduyn, P., Delaveau, P., Rotgé, J. Y., Kuppens, P., Van Mechelen, I., & Fossati, P. (2017). The neural basis of emotions varies over time: Different regions go with onset- and offset-bound processes underlying emotion intensity. *Social Cognitive and Affective Neuroscience, 12*(8), 1261–1271. https://doi.org/10.1093/scan/nsx051

Rimé, B. (2009). Emotion elicits the social sharing of emotion: Theory and empirical review. *Emotion Review, 1*(1), 60–85. https://doi.org/10.1177/1754073908097189

Rimé, B., Finkenauer, C., Luminet, O., Zech, E., & Philippot, P. (1998). Social sharing of emotion: New evidence and new questions. *European Review of Social Psychology, 9*, 145–189. https://doi.org/10.1080/14792779843000072

Scherer, K. R., & Wallbott, H. G. (1994). Evidence for universality and cultural variation of differential emotion response patterning. *Journal of Personality and Social Psychology, 66*, 310–328.

Schuyler, B. S., Kral, T. R. A., Jacquart, J., Burghy, C. A., Weng, H. Y., Perlman, D. M., et al. (2012). Temporal dynamics of emotional responding: Amygdala recovery predicts emotional traits. *Social Cognitive and Affective Neuroscience, 9*(2), 176–181. https://doi.org/10.1093/scan/nss131

Shafir, R., Schwartz, N., Blechert, J., & Sheppes, G. (2015). Emotional intensity influences pre-implementation and implementation of distraction and reappraisal. *Social Cognitive and Affective Neuroscience, 10*(10), 1329–1337. https://doi.org/10.1093/scan/nsv022

Sheppes, G., & Gross, J. J. (2011). Is timing everything? Temporal considerations in emotion regulation. *Personality and Social Psychology Review, 15*(4), 319–331. https://doi.org/10.1177/1088868310395778

Sheppes, G., Scheibe, S., Suri, G., & Gross, J. J. (2011). Emotion-regulation choice. *Psychological Science, 22*(11), 1391–1396. https://doi.org/10.1177/0956797611418350

Siegle, G. J., Granholm, E., Ingram, R. E., & Matt, G. E. (2001). Pupillary and reaction time measures of sustained processing of negative information in depression. *Biological Psychiatry, 49*(7), 624–636. https://doi.org/10.1016/S0006-3223%2800%2901024-6

Siegle, G. J., Steinhauer, S. R., Thase, M. E., Stenger, V. A., & Carter, C. S. (2002). Can't shake that feeling: Event-related fMRI assessment of sustained amygdala activity in response to emotional information in depressed individuals. *Biological Psychiatry, 51*(9), 693–707.

Sonnemans, J., & Frijda, N. H. (1994). The structure of subjective emotional intensity. *Cognition & Emotion, 8*(4), 329–350.

Tugade, M. M., & Fredrickson, B. L. (2004). Resilient individuals use positive emotions to bounce back from negative emotional experiences. *Journal of Personality and Social Psychology, 86*(2), 320–333. https://doi.org/10.1037/0022-3514.86.2.320

Van Mechelen, I., Verduyn, P., & Brans, K. (2013). The duration of emotional episodes. In D. Hermans, B. Rimé, & B. Mesquita (Eds.), *Changing emotions* (pp. 174–180). Psychology Press.

Verduyn, P., & Brans, K. (2012). The relationship between extraversion, neuroticism and aspects of trait affect. *Personality and Individual Differences, 52*(6), 664–669. https://doi.org/10.1016/j.paid.2011.12.017

Verduyn, P., Delaveau, P., Rotgé, J. Y., Fossati, P., & Van Mechelen, I. (2015). Determinants of emotion duration and underlying psychological and neural mechanisms. *Emotion Review, 7*, 330–335.

Verduyn, P., Delvaux, E., Van Coillie, H., Tuerlinckx, F., & Van Mechelen, I. (2009a). Predicting the duration of emotional experience: Two experience sampling studies. *Emotion, 9*(1), 83–91. https://doi.org/10.1037/a0014610

Verduyn, P., & Lavrijsen, S. (2015). Which emotions last longest and why: The role of event importance and rumination. *Motivation and Emotion, 39*(1), 119–127. https://doi.org/10.1007/s11031-014-9445-y

Verduyn, P., Van Mechelen, I., & Frederix, E. (2012a). Determinants of the shape of emotion intensity profiles. *Cognition and Emotion, 26*(8), 1486–1495. https://doi.org/10.1080/02699931.2012.662152

Verduyn, P., Van Mechelen, I., Kross, E., Chezzi, C., & Van Bever, F. (2012b). The relationship between self-distancing and the duration of negative and positive emotional experiences in daily life. *Emotion, 12*(6), 1248–1263. https://doi.org/10.1037/a0028289

Verduyn, P., Van Mechelen, I., & Tuerlinckx, F. (2011). The relation between event processing and the duration of emotional experience. *Emotion, 11*(1), 20–28. https://doi.org/10.1037/a0021239

Verduyn, P., Van Mechelen, I., Tuerlinckx, F., Meers, K., & Van Coillie, H. (2009b). Intensity profiles of emotional experience over time. *Cognition & Emotion, 23*(7), 1427–1443. https://doi.org/10.1080/02699930902949031

Verduyn, P., Van Mechelen, I., Tuerlinckx, F., & Scherer, K. (2013). The relation between appraised mismatch and the duration of negative emotions: Evidence for universality. *European Journal of Personality, 27*(5), 481–494. https://doi.org/10.1002/per.1897

Villano, W. J., Otto, A. R., Ezie, E. C., Gillis, R., & Heller, A. S. (2020). Temporal dynamics of real-world emotion are more strongly linked to prediction error than outcome. *Journal of Experimental Psychology: General, 149*(9), 1755–1766. https://doi.org/10.1037/xge0000740

Waugh, C. E., Hamilton, J. P., & Gotlib, I. H. (2010). The neural temporal dynamics of the intensity of emotional experience. *NeuroImage, 49*(2), 1699–1707. https://doi.org/10.1016/j.neuroimage.2009.10.006

Waugh, C. E., Shing, E. Z., & Avery, B. M. (2015). Temporal dynamics of emotional processing in the brain. *Emotion Review, 7*(4), 323–329. https://doi.org/10.1177/1754073915590615

Chapter 2

Appraisal Dynamics: A Predictive Mind Process Model Perspective

Jonas Everaert, James J. Gross, and Andero Uusberg

Abstract The dynamic updating and revising of appraisals affords a crucial measure of flexibility to emotion processing from emotion generation through emotion regulation. However, much remains to be understood about the specific computations underlying appraisal shifts in iterative cycles of emotion generation and emotion regulation. In this chapter, we argue that a predictive mind process model perspective, constituted by predictive coding and active inference accounts, can help to clarify when and how appraisals are updated and revised. We start with a brief overview of basic concepts underlying the extended process model of emotion regulation and the predictive mind perspective. Next, we recast the extended process model in predictive terms, yielding a novel framework for understanding appraisal as well as reappraisal. We finish by outlining implications of this framework for understanding temporal dynamics of emotion and emotion regulation as well as individual differences and clinical phenomena.

Direct contact to Jonas Everaert (j.everaert@tilburguniversity.edu).

J. Everaert (✉)
Department of Medical and Clinical Psychology, Tilburg University, Tilburg, The Netherlands

J. J. Gross
Department of Psychology, Stanford University, Stanford, CA, USA
e-mail: gross@stanford.edu

A. Uusberg
Institute of Psychology, University of Tartu, Tartu, Estonia
e-mail: andero.uusberg@ut.ee

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_2

2.1 Introduction

The way people cognitively appraise the motivational meaning of a situation shapes the type as well as intensity of their emotional responses (Ellsworth & Scherer, 2003; Lazarus, 1991). It also provides a pathway for regulating these responses (Uusberg et al., 2019; Yih et al., 2019). This latter point is important because as emotions come and go, the individual experiencing these emotions often evaluates them as being either helpful or unhelpful, pleasant or unpleasant. People may wish that an emotion such as joy would linger on, or that an emotion such as sadness would pass more quickly. As a result, people regularly try their hand at—and often succeed in—altering their emotions.

The process of appraisal involves weighing different aspects of a situation against idiographic goals on a relatively small set of appraisal dimensions to optimize one's response to situational demands (Kuppens, 2013; Mehu & Scherer, 2015). Commonly proposed appraisal dimensions (Moors et al., 2013; Scherer, 2001) include *relevance* (the importance of a situation to the individual's goals), *congruence* (the helpfulness of a situation with respect to these goals), *likelihood* (the certainty about the current status and future prospects of the situation), *agency* (the attribution of accountability for the situation), as well as problem- and emotion-focused *coping potential* (the control or power to change the situation). The appraisal process produces a pattern of evaluations along such dimensions that shapes the nature of the emotional episode (Gross, 1999; Koole, 2009).

Because situations and goals evolve over time, people need to *update* their appraisals to reflect such changes. For instance, a charging dog in a park can initially be appraised as threating and then as benign once it becomes clear that it is on a leash. People also *revise* their appraisals in order to meet emotion regulatory goals. The dog on a leash can be re-appraised as threatening in order to justify one's outburst of anger at the owner. The dynamic updating and revising of appraisals afford flexibility to emotion as a process from generation to regulation. While recent contributions have started to consider appraisal dynamics (Mehu & Scherer, 2015; Uusberg et al., 2019; Yih et al., 2019), much remains to be understood about the specific computations underlying appraisal shifts in iterative cycles of emotion generation and regulation that both shape and are shaped by environmental and goal-related changes.

In this chapter, we argue that 'predictive coding' and 'active inference' accounts, collectively constituting a predictive mind process model perspective, can help to clarify when and how appraisals are updated and revised. We start with a brief overview of basic concepts underlying the extended process model of emotion regulation and the predictive mind perspective. Next, we recast the extended process model in predictive terms yielding a novel framework for understanding appraisal as well as reappraisal. We finish by outlining implications of this framework for understanding temporal dynamics of emotion and emotion regulation as well as individual differences and clinical phenomena.

2.2 The Extended Process Model (EPM) of Emotion Regulation

The EPM views emotion generation and regulation as arising from interacting valuation systems that output actions for achieving desired states based on perceptual input (Gross, 2015; Sheppes et al., 2015). As depicted in Fig. 1, the EPM envisions valuation systems as a cascade of processes with four key steps. These are: the current state of the internal or external World (W), perception of that world (P), appraisal or valuation of these perceptions in relation to goals (V), and actions selected to reduce any discrepancy between the goal states and perceived state of the world (A). The World-Perception-Valuation-Action (WPVA) cycles operate iteratively enabling an individual to adaptively respond to changing goals and environments.

Within the EPM, emotion generation is viewed as a first-level WPVA cycle. During this cycle, a person monitors the current situation (W_1), perceives the situation while attending to potentially significant aspects of it (P_1), and appraises these aspects in light of goals (V_1). The resulting appraisals produce a coordinated set of experiential, physiological, and behavioral responses that constitute an emotional response (A_1). For example, the emotion of dissatisfaction may arise when a person delivers a presentation at a conference (W_1), allocates attention to members of the audience who are frowning or looking on their smartphones (P_1), appraises the situation as a missed opportunity to make a good impression (V_1), and feels as well as expresses sadness (A_1).

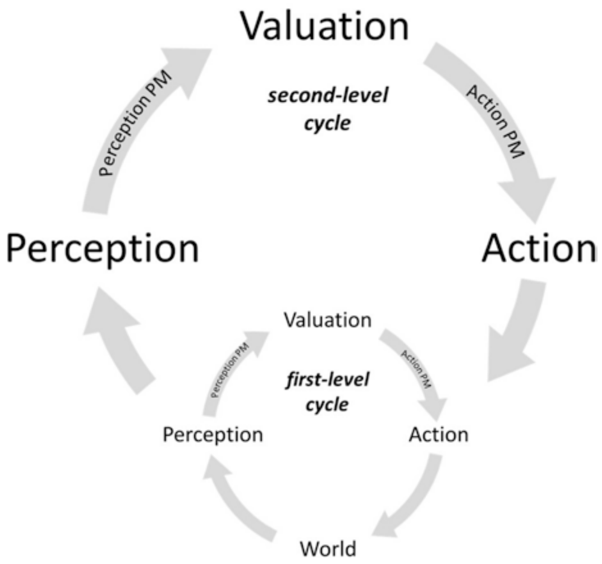


Fig. 1 The iterative process of appraising changing situations

Emotion regulation is viewed in the EPM as a second-level $WPVA_2$ cycle that modulates the first-level emotion-generating $WPVA_1$ cycle. The emotion-regulation $WPVA_2$ cycle takes the state of the emotion-generation $WPVA_1$ cycle as its input (W_2). Within the second-level cycle, a person perceives and attends to the current emotional state (P_2) and compares it to a desired emotional state (V_2). When there is a sufficiently large discrepancy between perceived and desired emotion, a person may initiate regulation strategies to modulate the state of the first-level system (A_2). These regulation strategies may change subsequent iterations of the first-level emotion-generative $WPVA_1$ cycle by intervening at one or more of its steps. Emotion regulation may influence emotion by *changing* which *situations* are encountered or how they unfold (W_1), *changing* which aspects of the situation are *attended* by reallocating attention resources between emotionally relevant and irrelevant aspects of a situation (P_1), *changing* how a situation is *appraised* by altering how it is construed or which goals it is compared to (V_1), or *changing* the emotional *response* by influencing its experiential, physiological, or behavioral components (A_1). This second-level $WPVA_2$ cycle is repeated until the discrepancy between perceived and desired emotion is sufficiently reduced or the goal to reduce it is abandoned. The cycle may involve processes that operate automatically to influence which emotions are experienced and only require few iterations. Alternatively, the cycle may involve deliberate attempts to find and successfully deploy a strategy, resulting in slower emotion regulation (Webb et al., 2015).

2.3 The Predictive Mind (PM) Perspective

A number of models and theories are beginning to coalesce into an overarching perspective that highlights the role of predictive processes in understanding not only perception and action but also cognition and emotion (Barrett & Simmons, 2015; Clark, 2013; Friston, 2010; Seth, 2013). At the heart of the predictive mind (PM) perspective is the idea that the mind builds mental models of the external and internal world and uses these models to recognize what it senses, how to think about it, and how to act upon it. Relating different functions of the mind to a common computational theme allows the PM perspective to characterize perception and action using a single set of concepts such as mental models, sensory data, precision, prediction errors, and error minimization (Seth, 2013; Uusberg et al., 2020).

The *PM account of perception* (i.e., predictive coding or predictive processing) assumes that the mind implements empirical Bayesian hypothesis testing and updating cycles to produce increasingly accurate models of the world (Clark, 2013; Friston, 2010). Prior experience has equipped the mind with mental models of the world (*priors* in Bayesian statistical terms, beliefs in cognitive psychology terms) that can be used within a context to generate predictions about sensory data and, in effect, to explain these data in terms of their causes (Friston et al., 2006). Predictions derived from mental models are tested against sensory data yielding a discrepancy measure: a prediction error. Large prediction errors provide corrective feedback that can be used to update mental models until one is found that minimizes the prediction errors (Barrett & Simmons, 2015). Small or non-existent prediction errors thus function as evidence that a mental model is an accurate representation of the world. Mental models that yield the smallest prediction errors in relation to current sensory input populate our perceptual reality.

According to the predictive mind perspective, the mind continuously strives to minimize prediction errors. The degree to which mental models are updated in this process depends on the precision of the model relative to the data. Precision refers to certainty, or the probability with which the mind takes the mental model or the sensory data to be reliable representations of reality. Prediction error minimization is governed by precision weighting whereby more credit is given to more reliable information sources and noisy sources are down-weighted. If a mental model is represented as highly precise, then it will be adjusted only slightly even in the presence of conflicting sensory data yielding a prediction error. Conversely, if the model thought to have low precision, then it will be updated in the direction of the sensory data.

The *PM account of action* (i.e., active inference) suggests that the same constructs of mental models, prediction errors, and error minimization are instrumental for controlling goal-directed behavior (including behavioral components of perception). According to this view, actions produce changes to the world that minimize another version of prediction errors: discrepancies between how the world is and how it is requested to be by the action control system (Friston, 2010; Friston et al., 2016; Seth, 2013). Actions are taken to be represented in the mind not merely as collections of motor commands, but as collections of predicted sensory consequences of motor commands, or action outcomes. This allows action control systems to compute errors between predicted action outcomes and desired states of the world. For instance, a driver wishing to turn left can use her prior experience to predict the outcomes of turning the steering wheel to the right and to the left, observe the discrepancies between each action and the desired state of the car moving leftwards, and proceed with turning the steering wheel to left given its smaller action outcome prediction error. Different actions can thus be evaluated based on their capacity to minimize action outcome prediction errors until an action is found that gets closest to realizing the desired state in the world (Adams et al., 2013). Predictive action control enables the mind to flexibly initiate successive actions across the motor hierarchy that are tuned to overcome discrepancies between the current state and the desired state of the world.

2.4 A Predictive Mind Process Model Perspective

We propose that the PM framework helps to characterize key computations that are involved in the *updating and revising of* appraisals during Valuation after receiving new information within both first-level and second-level WPVA cycles. As the internal and external environment continuously changes ($W_{1.1} \rightarrow W_{1.2}$), people must update their mental models of the World by selecting relevant features of the environment for further processing ($P_{1.1}$) and then appraising the perceived input ($V_{1.1}$). New information ($W_{1.2}$) that enters the perceptual system ($P_{1.2}$) may be consistent or inconsistent with the initial appraisal ($V_{1.1}$) and either rejected or integrated into an updated appraisal ($V_{1.2}$). This has the potential to generate dynamics within emotional responses ($A_{1.1} \rightarrow A_{1.2}$) that shape the way people behave, leading in turn to changes to the internal and external environment. At times, the unfolding emotion-generative process may instigate parallel second-level multi-stage emotion regulation WPVA cycles that serve to modulate the first-level cycles. Within both cycles, mental models are continuously compared against new information that becomes available when situations and emotions dynamically unfold over time.

Novel insights into the iterative unfolding of emotion generation and regulation can be gained from realizing that the processes that connect different steps of WPVA cycles are well characterized by the predictive mind perspective. Specifically, we argue that each link in the W to P to V to A to W cycle can be thought of as a prediction error reduction process, either of the perceptual or action kind. Perceptual prediction error reduction enables valuation systems to generate a stable representation (P) of their input (W). Likewise, action prediction error reduction enables valuation systems to control behavior so that a requested action (A) has an impact on the world (W). As the W to P and A to W links within valuation systems correspond, respectively, to perception and action control, our proposal thus far simply re-states the core premises of the predictive mind perspective. Our proposal goes beyond existing accounts by offering a predictive mind perspective of appraisal processes. Specifically, we suggest that *appraisal involves both perceptual and action aspects that can be thought of as the P to V and V to A links within WPVA* cycles *of emotion generation and regulation, served respectively by perceptual and action predictive error reductions*. Figure 1 shows the perception and action PM components of appraisal within the WPVA cycle.

Perceptual error minimization links P to V in the WPVA cycle by representing the motivational meaning of the perceptual construal (P) of the world using a relatively abstract appraisal (V). A pattern of evaluations on appraisal dimensions can be viewed as a relatively abstract mental model that represents the core relational themes within the situation. Core relational themes refer to broad kinds of person-environment relationships in terms of their motivational meaning, such as harm, benefit, threat, loss or helplessness (Lazarus, 1991; Nezlek et al., 2008; Smith & Lazarus, 1993). As such, these appraisals represent functional dimensionality reduction processes, distilling the motivational essence of a situation.

We suggest that core relational themes become activated as the P to V step within a WPVA cycle compares predictions derived from candidate themes with perceptual construals of the situation (rather than raw sensory input). For instance, a situation construed as “a dog charging at me” aligns with predictions from an abstract appraisal of “a threatening situation”. Prediction error between appraisal patterns and construals are then used to either settle on an appraisal pattern or alter it, depending on the precision afforded to the construal and the appraisal pattern based on prior experience. More precise perceptual information will shift the appraisal outcome toward the construal. For instance, clearly seeing that the dog is on a leash reduces the threat appraisal. By contrast, more precise appraisal patterns will shift the appraisal outcome toward the activated core relational theme. For instance, prior experience with dogs escaping their leash maintains the threat appraisal. This appraisal-feedback process stabilizes once probable core themes have been inferred from perceived input.

Moreover, *action error minimization links V to A in the WPVA cycle* by translating the motivational properties of appraisals (V) into action tendencies (A) that can go on to affect the World (W). Appraisal patterns are higher-order semantic models that help explain the world that also function as relatively abstract goals. For instance, appraising a situation as threatening also functions as a goal to somehow neutralize the threat. Each appraisal dimension may encompass a different higher-order goal: motive relevance may encompass a desire for immediate rather than delayed action, and self-accountability may lead to a desire to change oneself rather than others (Roseman, 2013). Appraisal (V) thus provides desired end states that are translated by lower-order action prediction error reduction processes into more situation-specific action tendencies (V to A) (Eder & Rothermund, 2013). Given a desired end state, different action options are evaluated with respect to their predicted capacity to minimize the mismatch between the current and the desired state. This comparison produces a prediction error that affects the value of an action option (Ridderinkhof, 2017). This valuation of action optimizes the selection of the action (A) that is adequate to accomplish the changes in the world (W) and reach the desired end state prescribed by appraisal (V).

Casting the P-V and V-A steps of the WPVA cycle, and the appraisal processes within it, in PM terms has implications for the dynamic aspects of both emotion generation and regulation. At the first-level WPVA cycles, the initial valuation step forms an initial appraisal ($V_{1.1}$) by weighing perceptions ($P_{1.1}$) of salient features (e.g., a robber with a gun) of a particular situation ($W_{1.1}$, e.g., a bank robbery) and activated core relational themes (e.g., facing an uncertain, existential threat). When situations are new to people, their initial appraisal may be particularly driven by the activated core relational theme because the precision of construal has not yet had time to accumulate. The initial appraisal $V_{1.1}$ in turn shapes emotional responses ($A_{1.1}$) such as feelings (e.g. anxiety), action tendencies (e.g. to flee), and attention allocation to anticipated features (e.g., look at and attend to the robber to determine whether he/she is carrying a gun).

Attention allocation, as an epistemic action, is particularly instrumental in guiding appraisal and emotion dynamics. As appraisals of relevance as well as uncertainty function as a goal to gain more information (e.g., assess the current exposure to threat), information sources that are anticipated to provide more precise information (e.g., the hands of the robber) are preferentially sampled, while those that are expected to provide imprecise information (e.g., the feet of the robber) are ignored (Maratos & Pessoa, 2019; Parr & Friston, 2018). The resulting new perceptions ($P_{1.2}$, e.g., the robber is unarmed) of the world becomes data that is compared with the initial appraisal ($V_{1.1}$). Prediction errors between the initial appraisal $V_{1.1}$ and new construal ($P_{1.2}$) are resolved through precision weighing to determine the extent to which the initial appraisal is updated. The resulting appraisal ($V_{1.2}$) will again modulate the elicited emotional response (e.g., relief) and guide attention allocation to relevant stimuli ($A_{1.2}$), which in turn influences what is sensed from the World ($W_{1.3}$), etc.

At the second-level WPVA cycles, the emotion generated by the first-level WPVA cycle is first represented using perceptual prediction error minimization. Specifically, an emotion concept ($P_{2.1}$, e.g., anxiety) is activated that can predict with minimal errors the interoceptive and meta-cognitive information available about the current emotion ($W_{2.1}$, e.g., sympathetic arousal coupled with unpleasant feeling). Next, perceptual prediction error minimization is also used to relate the represented emotion to more abstract mental models of the motivational meaning of emotional states, or "emotion relational themes" ($V_{2.1}$; e.g., anxiety can impair judgement and should be lowered; Tamir & Millgram, 2017). This suggests that the adaptive dynamics of emotion regulation depend on the availability of sufficiently granular mental models to represent the ongoing emotional states and their motivational meaning (Kashdan et al., 2015). The second-level WPVA cycle proceeds by using action prediction error minimization to select and implement a regulatory action. In the V to A step, the predicted outcomes of regulatory action options are compared to the desired change in emotion inherent in its motivational meaning ($V_{2.1}$; e.g., reduce anxiety to a more manageable level). The regulatory action promising the largest extent of error minimization ($A_{2.1}$; e.g., do a deep breathing exercise) is selected and then implemented in the A to W step with the aim of producing changes to the first-level emotion-generative system ($W_{2.2}$; e.g., attenuated sympathetic arousal coupled with less unpleasant feeling).

Within the PM perspective on WPVA cycles, perceptual and action PM processes are intimately related as they continuously interact over time (see Fig. 1). Perception PM processes provide input for action PM processes, which in turn, through producing changes to the world and to the emotion, shape the input for perception PM processes. Appraisal processes serve as a hub between perception and action PM. They do this by enabling the engagement of relatively abstract models of key features of the situation and of the emotion and preferentially linking these to relatively abstract models of actions that will bring the state of the world and the state of the mind into alignment with desired state. In this way, appraisal processes involved in emotion and emotion regulation play a critical role in integrating and coordinating perception and action to guide inference and learning.

2.5 Implications for Understanding Temporal Dynamics of Emotion and Emotion Regulation

The PM perspectives on perception and action during WPVA cycles of emotion generation and regulation help to explain how appraisal relates to temporal dynamics of emotion and emotion regulation. At the level of *emotion*, perceptual and action PM mechanisms may account for specific patterns of moment-to-moment *emotion dynamics*, including emotional inertia and instability. At the level of emotion regulation, perceptual and action PM mechanisms may account for specific patterns of moment-to-moment emotion regulation *dynamics*, including emotion regulation inertia and instability (which, in turn, shape emotion dynamics). In what follows, we consider each of these ideas in turn.

At the level of *emotion*, emotional inertia refers to increased moment-to-moment predictability of emotional states across time and situations (Kuppens et al., 2010). Inertia of emotions may occur when greater precision is afforded to prior models compared to the perceptual input (i.e., *strong prior model hypothesis*). Highly precise predictions derived from core relational themes (e.g., low coping potential in situations of danger or threat) may shift the appraisal process toward the model. An overreliance on prior models will result in a high level of stability in appraisal patterns over time at the cost of integrating perceptual evidence sampled from the world. Consequently, appraisals lose their adaptive sensitivity and may consistently elicit similar emotions regardless of important nuances in the context (Mehu & Scherer, 2015).

Action PM processes may further reinforce this pattern of rigidity in emotional responding over time in two ways. First, the stable appraisal outcome may set the stage for active perceptual inferences that increases the likelihood of generating perceptual input that is consistent with the model (e.g., by guiding attention to particular cues). Highly precise models may thus guide perceptual behavior to the detriment of new observations and prediction errors that would correct the model's predictions during perceptual PM, as such fueling emotional inertia. Second, the stable appraisal outcome may also generate stable action tendencies across slightly different situations that nudge these situations to unfold in a converging manner (e.g., an aggressive action tendency escalates interpersonal conflict). Highly precise appraisal models may thus also contribute to emotional inertia by shaping initially diverse situations to become more similar.

At the level of *emotion*, perceptual and action PM processes may also account for *emotional* instability, which refers to the magnitude of moment-to-moment emotional changes (Kuppens et al., 2010). Emotional instability may occur when there is an overreliance on sensory evidence (i.e., *weak prior model hypothesis*). The persistent prediction errors force internal models to change constantly based on situation-specific features of the current context. The internal model of situational appraisals lacks stability and does not progress toward a model that is able to predict and thereby explain the world. This instability in the internal model may produce emotional responses that differ in magnitude each time the internal model is updated during WPVA cycles, resulting in emotional instability. The unstable nature of the models may render them less potent in informing model-guided perception toward relevant cues in the world during action PM. As a result, only limited model-congruent information enters perception to update the model during perceptual PM, instigating a vicious cycle.

At the level of emotion regulation, action PM determines which regulation strategy is selected by weighing the desired emotional state and the anticipated changes in emotion associated with a particular emotion regulation strategy. Beliefs about the malleability of (components of) emotions (Tamir et al., 2007) as well as by beliefs about the effectiveness of emotion regulation strategies may determine whether emotion regulation is attempted, and if so, may guide the selection of the optimal strategy to achieve the desired emotional state within a given context (Sheppes et al., 2014). For example, when someone believes that feelings of shame and anxiety are difficult to control once elicited, one may engage in efforts to avoid or escape the emotion-eliciting stimulus (e.g., avoiding particular places). The perceived effects of the regulatory attempt (i.e., the experienced (lack of) changes in emotion) will be compared to the model's predictions of the expected change in emotions. This discrepancy (prediction error) informs the system whether to keep using the selected strategy or change it to achieve the desired emotional state.

Highly precise expectations regarding emotion malleability and the effectiveness of the selected emotion regulation strategy (*strong prior model hypothesis*) may lead to emotion regulation inertia by discarding the actual data about the (lack of) change(s) in the targeted emotional state. Because the expectations are not brought into congruence with the perceived evidence, more rigid or inflexible patterns of emotion regulation strategy use could emerge. For example, when someone is convinced that thinking frequently about his/her feelings of sadness increases the understanding of one's problems, then this person will likely maintain repetitive negative thinking even though this strategy maintains negative affect. By contrast, when more precision is afforded to the perceived (lack of) change(s) in the targeted emotion (*weak prior model hypothesis*), it is more likely that such an integration of evidence and model's predictions encourages greater flexibility in selecting an emotion regulation strategy from the repertoire (Bonanno & Burton, 2013). This is because valuations will shift more toward the experienced emotional state and the model including predictions of the effectiveness associated with the implemented emotion regulation strategy will be adjusted. The updated model may inform switches in the selection of the emotion regulation strategy in subsequent WPVA cycles.

2.6 Implications for Understanding Individual Differences and Clinical Phenomena

This predictive mind view on appraisal dynamics has interesting implications for understanding sources of individual differences in temporal characteristics of appraisal, emotion, and emotion regulation. Personality traits and psychopathology are often associated with individual differences in tendencies to appraise situations, as such setting the stage for altered patterns of emotion and emotion regulation dynamics (Everaert et al., 2020; Gross et al., 2019; Kuppens & Van Mechelen, 2007; Mehu & Scherer, 2015; Scherer, 2020).

Research on the relation between personality and appraisal tendencies suggests that neuroticism is related to a tendency to appraise situations as being negative and low in coping potential (Tong, 2010, p. 20), whereas traits such as conscientiousness and agreeableness are related to tendencies to appraise situations as being negative and relevant to the individual's current goals (Scherer, 2020). Furthermore, studies have shown that personality traits are meaningfully related to individual differences in decisions made during the identification, selection, and implementation stages of emotion regulation (Hughes et al., 2020). The proposed predictive mind perspective may shed light on how personality traits are linked to biased appraisal patterns and associated emotion and emotion regulation dynamics.

We propose that configurations of personality traits (e.g., high on neuroticism and low on extraversion) may be associated with lower activation thresholds of particular core relational themes (e.g., themes related to harm, danger, uncertainty, or threat). When activated, these core relational themes may receive higher precision compared to perceptual information, so that prediction errors are resolved by discarding (inconsistent) perceptual information. Over time, the overreliance on the model may set the stage for distorted emotion dynamics (e.g., inertia of negative emotions such as anxiety). In addition, personality variables may be associated with a particular set of beliefs about the malleability of emotional responses and efficacy of particular strategies (e.g., neuroticism may be linked to avoidance of potentially threatening situations), thereby skewing action PM processes serving the selection of emotion regulation strategy to alter the elicited emotional response. To explore these possibilities, future research could examine how personality traits are related to central concepts of the action and perception PM perspective on appraisal dynamics.

Research on psychopathology has frequently documented that common disorders such as depression are associated with disturbances in emotion dynamics and emotion regulation strategy use. Depression has been linked to emotional inertia (Kuppens et al., 2010) and rigidity in the use of emotion regulation strategies such as rumination and dampening of positive emotions (Bean et al., 2020; Vanderlind et al., 2021). The action and perception PM perspective on appraisal dynamics provides a potential explanation for factors underlying this rigidity in emotion dynamics and emotion regulation. In particular, depression may be associated with highly precise prior models during perception PM (e.g., a core relational theme related to irrevocable loss) and action PM (e.g., beliefs that certain emotion regulation strategies are appropriate or effective to achieve a goal) so that inconsistent input is consistently ignored, instigating rigidity at the level of emotion and emotion regulation over time. We think that this PM perspective provides a valuable framework to investigate psychopathology-related individual differences in imbalances of weighing precisions of predictions and data to understand individual differences in maladaptive temporal dynamics of emotion and emotion regulation.

2.7 Concluding Comment

This chapter proposes that appraisal dynamics that at the heart of emotion and emotion regulation dynamics can be understood by linking the extended process model of emotion regulation with the predictive mind perspective. We illustrated how predictive coding and active inference explain the dynamic changes in appraisals based on prediction error, precision weighing, and error minimization through either updating predictions or performing actions that produce changes in line with predictions. Moreover, we argued that imbalances in precisions afforded to predictions versus data might explain how appraisal dynamics shape temporal dynamics of emotion generation and regulation. Finally, we elaborated on how the proposed predictive mind view could be leveraged to better understand personality and psychopathology as sources of individual differences in appraisal patterns, emotions, and emotion regulation. Future research should explore the utility of predicting coding and active inference accounts to model the (sources of) temporal dynamics of appraisal patterns, emotions, and emotion regulation.

Acknowledgement This work was supported by a postdoctoral fellowship from the Research Foundation Flanders (1202119N) awarded to Jonas Everaert and Estonian Research Council grant PSG525 awarded to Andero Uusberg.

References

Adams, R. A., Shipp, S., & Friston, K. J. (2013). Predictions not commands: Active inference in the motor system. *Brain Structure & Function, 218*(3), 611–643. https://doi.org/10.1007/s00429-012-0475-5

Barrett, L. F., & Simmons, W. K. (2015). Interoceptive predictions in the brain. *Nature Reviews Neuroscience, 16*(7), 419–429. https://doi.org/10.1038/nrn3950

Bean, C. A. L., Heggeness, L. F., Kalmbach, D. A., & Ciesla, J. A. (2020). Ruminative inertia and its association with current severity and lifetime course of depression. *Clinical Psychological Science*. Retrieved October 21, 2020, from https://journals.sagepub.com/doi/full/10.1177/2167702620949174

Bonanno, G. A., & Burton, C. L. (2013). Regulatory flexibility. *Perspectives on Psychological Science, 8*(6), 591–612. https://doi.org/10.1177/1745691613504116

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences, 36*(3), 181–204. https://doi.org/10.1017/S0140525X12000477

Eder, A. B., & Rothermund, K. (2013). Emotional action: An ideomotor model. In *Handbook of psychology of emotions (Vol 1): Recent theoretical perspectives and novel empirical findings* (pp. 11–38). Nova Science Publishers.

Ellsworth, P. C., & Scherer, K. R. (2003). Appraisal processes in emotion. In *Handbook of affective sciences* (pp. 572–595). Oxford University Press.

Everaert, J., Bronstein, M. V., Castro, A., Cannon, T. D., & Joormann, J. (2020). When negative interpretations persist, positive emotions don't! Inflexible negative interpretations encourage depression and social anxiety by dampening positive emotions. *Behaviour Research and Therapy, 124*.

Friston, K. J. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience, 11*(2), 127–138. https://doi.org/10.1038/nrn2787

Friston, K. J., FitzGerald, T., Rigoli, F., Schwartenbeck, P., O'Doherty, J., & Pezzulo, G. (2016). Active inference and learning. *Neuroscience & Biobehavioral Reviews, 68*, 862–879. https://doi.org/10.1016/j.neubiorev.2016.06.022

Friston, K. J., Kilner, J., & Harrison, L. (2006). A free energy principle for the brain. *Journal of Physiology-Paris, 100*(1), 70–87. https://doi.org/10.1016/j.jphysparis.2006.10.001

Gross, J. J. (1999). Emotion regulation: Past, present, future. *Cognition and Emotion, 13*(5), 551–573. https://doi.org/10.1080/026999399379186

Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological Inquiry, 26*(1), 1–26. https://doi.org/10.1080/1047840X.2014.940781

Gross, J. J., Uusberg, H., & Uusberg, A. (2019). Mental illness and well-being: An affect regulation perspective. *World Psychiatry, 18*(2), 130–139. https://doi.org/10.1002/wps.20618

Hughes, D. J., Kratsiotis, I. K., Niven, K., & Holman, D. (2020). Personality traits and emotion regulation: A targeted review and recommendations. *Emotion, 20*(1), 63–67. https://doi.org/10.1037/emo0000644

Kashdan, T. B., Barrett, L. F., & McKnight, P. E. (2015). Unpacking emotion differentiation: Transforming unpleasant experience by perceiving distinctions in negativity. *Current Directions in Psychological Science, 24*(1), 10–16. https://doi.org/10.1177/0963721414550708

Koole, S. L. (2009). The psychology of emotion regulation: An integrative review. *Cognition & Emotion, 23*(1), 4–41. https://doi.org/10.1080/02699930802619031

Kuppens, P. (2013). Comment: Appraisal affords flexibility to emotion in more ways than one. *Emotion Review, 5*(2), 176–179. https://doi.org/10.1177/1754073912468167

Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010). Emotional inertia and psychological maladjustment. *Psychological Science, 21*(7), 984–991. https://doi.org/10.1177/0956797610372634

Kuppens, P., & Van Mechelen, I. (2007). Interactional appraisal models for the anger appraisals of threatened self-esteem, other-blame, and frustration. *Cognition and Emotion, 21*(1), 56–77. https://doi.org/10.1080/02699930600562193

Lazarus, R. S. (1991). *Emotion and adaptation (pp. xiii, 557)*. Oxford University Press.

Maratos, F. A., & Pessoa, L. (2019). What drives prioritized visual processing? A motivational relevance account. In N. Srinivasan (Ed.), *Progress in brain research* (Vol. 247, pp. 111–148). Elsevier. https://doi.org/10.1016/bs.pbr.2019.03.028

Mehu, M., & Scherer, K. R. (2015). The appraisal bias model of cognitive vulnerability to depression. *Emotion Review, 7*(3), 272–279. https://doi.org/10.1177/1754073915575406

Moors, A., Ellsworth, P. C., Scherer, K. R., & Frijda, N. H. (2013). Appraisal theories of emotion: State of the art and future development. *Emotion Review, 5*(2), 119–124. https://doi.org/10.1177/1754073912468165

Nezlek, J. B., Vansteelandt, K., Van Mechelen, I., & Kuppens, P. (2008). Appraisal-emotion relationships in daily life. *Emotion, 8*(1), 145–150. https://doi.org/10.1037/1528-3542.8.1.145

Parr, T., & Friston, K. J. (2018). Active inference, novelty and neglect. *Current Topics in Behavioral Neurosciences, 41*, 115–128.

Ridderinkhof, K. R. (2017). Emotion in action: A predictive processing perspective and theoretical synthesis. *Emotion Review, 9*(4), 319–325. https://doi.org/10.1177/1754073916661765

Roseman, I. J. (2013). Appraisal in the emotion system: Coherence in strategies for coping. *Emotion Review, 5*(2), 141–149.

Scherer, K. R. (2001). Appraisal considered as a process of multilevel sequential checking. In *Appraisal processes in emotion: Theory, methods, research* (pp. 92–120). Oxford University Press.

Scherer, K. R. (2020). Evidence for the existence of emotion dispositions and the effects of appraisal bias. *Emotion*. https://doi.org/10.1037/emo0000861

Seth, A. K. (2013). Interoceptive inference, emotion, and the embodied self. *Trends in Cognitive Sciences, 17*(11), 565–573. https://doi.org/10.1016/j.tics.2013.09.007

Sheppes, G., Scheibe, S., Suri, G., Radu, P., Blechert, J., & Gross, J. J. (2014). Emotion regulation choice: A conceptual framework and supporting evidence. *Journal of Experimental Psychology General, 143*(1), 163–181. https://doi.org/10.1037/a0030831

Sheppes, G., Suri, G., & Gross, J. J. (2015). Emotion regulation and psychopathology. *Annual Review of Clinical Psychology, 11*, 379–405. https://doi.org/10.1146/annurev-clinpsy-032814-112739

Smith, C. A., & Lazarus, R. S. (1993). Appraisal components, core relational themes, and the emotions. *Cognition and Emotion, 7*(3–4), 233–269. https://doi.org/10.1080/02699939308409189

Tamir, M., John, O. P., Srivastava, S., & Gross, J. J. (2007). Implicit theories of emotion: Affective and social outcomes across a major life transition. *Journal of Personality and Social Psychology, 92*(4), 731–744. https://doi.org/10.1037/0022-3514.92.4.731

Tamir, M., & Millgram, Y. (2017). Motivated emotion regulation: Principles, lessons, and implications of a motivational analysis of emotion regulation. In *Advances in motivation science* (pp. 207–247). Elsevier Academic Press.

Tong, E. M. W. (2010). Personality influences in appraisal-emotion relationships: The role of neuroticism. *Journal of Personality, 78*(2), 393–417. https://doi.org/10.1111/j.1467-6494.2010.00620.x

Uusberg, A., Suri, G., Dweck, C. S., & Gross, J. J. (2020). Motivation: A valuation systems perspective. Presented at the Nebraska Symposium on Motivation.

Uusberg, A., Taxer, J. L., Yih, J., Uusberg, H., & Gross, J. J. (2019). Reappraising reappraisal. *Emotion Review, 11*(4), 267–282. https://doi.org/10.1177/1754073919862617

Vanderlind, W. M., Everaert, J., & Joormann, J. (2021). Positive emotion in daily life: Emotion regulation and depression. *Emotion*. Advance online publication. https://doi.org/10.1037/emo0000944

Webb, T. L., Totterdell, P., & Ibar, D. N. H. (2015). Foundations and extensions for the extended model: More on implicit and explicit forms of emotion regulation. *Psychological Inquiry, 26*(1), 123–129. https://doi.org/10.1080/1047840X.2015.960040

Yih, J., Uusberg, A., Taxer, J. L., & Gross, J. J. (2019). Better together: A unified perspective on appraisal and emotion regulation. *Cognition & Emotion, 33*(1), 41–47. https://doi.org/10.1080/02699931.2018.1504749

Chapter 3
The Neuroscience of Affective Dynamics

Nikki A. Puccetti, William J. Villano, and Aaron S. Heller

Abstract Emotions are time-varying internal states that emerge, persist, and decay to promote survival in the face of dynamic environments and shifting homeostatic needs. Research in non-human organisms has recently afforded specific insights into the neural mechanisms that support the emergence, persistence, and decay of affective states. Concurrently, a separate affective neuroscience literature has begun to dissect the neural bases of affective dynamics in humans. However, the circuit-level mechanisms identified in animals lack a clear mapping to the human neuroscience literature. As a result, critical questions pertaining to the neural bases of affective dynamics in humans remain unanswered. To address these shortcomings, the present review integrates findings from humans and non-human organisms to highlight the neural mechanisms that govern the temporal features of emotional states. Using the theory of affective chronometry as an organizing framework, we describe the specific neural mechanisms and modulatory factors that ultimately arbitrate the rise-time, intensity, and duration of emotional experiences.

3.1 Introduction

Although there are multiple definitions of emotion, we and others define an emotion as a phasic response to a stimulus. Adolphs and Anderson further define an emotion as an internal (central nervous system) state following a specific event from which subjective, behavioral, and physiological outputs emerge (Anderson & Adolphs, 2014; Frijda, 1988; Scherer, 2005). This definition distinguishes emotions from moods or attitudes, for example, which are more enduring and may not have specific precipitants. Moreover, an emotion can be caused by stimuli either extrinsic or intrinsic to the organism. Evolutionarily, emotions are thought to be adaptive as they prime approach or avoidance behaviors to aversive or appetitive events, respectively.

N. A. Puccetti · W. J. Villano · A. S. Heller (✉)
Department of Psychology, University of Miami, Coral Gables, FL, USA
e-mail: aheller@miami.edu

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_3

As noted throughout this volume, emotions are inherently dynamic responses that vary around one's baseline state. As the rewards and threats in an organism's environment change, its behavioral responses must change as well. Thus, emotional states persist or decay relative to changes in an organism's external or intrinsic homeostatic environment (Heller, 2018). These emotional states naturally decay over time and return to the organism's "baseline" state, or homeostatic set point. However, emotional responses to personally relevant salient stimuli may also persist, even long after the emotion-evoking stimulus dissipates.

Such emotional dynamics emerge from patterns of neuronal activity (Anderson & Adolphs, 2014; LeDoux, 2000; Panksepp, 2011). Therefore, researchers interested in understanding the nature and dynamics of emotions must also characterize their underlying neural mechanisms. Across species, the emergence of emotional dynamics depends on several evolutionarily conserved neural mechanisms.

First, emotional states emerge and endure through persistent neural activity (Major & Tank, 2004). Persistent neural activity fundamentally underlies central internal states that yield physiological, behavioral, and cognitive changes associated with emotion. Depending on the response, an emotional state may be instantiated via persistent neural activity within a single region of the brain (e.g., the amygdala), or via persistent activity within an interconnected network of brain regions.

Second, emotions are not specific to single regions or circuits. Distinct brain regions or subnuclei within the same region can support opposing emotional responses (Berridge, 2019). Thus, specific brain activity patterns between regions can also explain the dynamics of internal emotional states. These patterns include synchronous activity and phasic entrainment between regions. As discussed below, these patterns of coordinated activity support the transmission of information throughout the brain, and the emergence of internal emotional states.

Third, the dynamics of emotional states are modulated by the release of neurotransmitters. Neurotransmitters fundamentally alter the properties, firing patterns, and behavioral outputs of neural circuits (Marder, 2012). Thus, a single population of neurons might contribute to two entirely different emotional responses depending on neurotransmitter concentration. Broadly, neurotransmitter activity enables coordinated, global shifts from baseline states to states associated with emotional responding.

3.1.1 Affective Chronometry

The model of affective chronometry provides a guiding theoretical framework to characterize the temporal features of emotional responses (Davidson, 1998; Solomon & Corbit, 1974; Tomkins, 1978). The three primary parameters on which the emotional time course varies are: (1) rise-time, or the latency between stimulus onset and the peak of an emotional response, (2) amplitude, or the peak of an emotional response, and (3) duration, or the length of time before an emotional response returns to baseline. As has been suggested, emotional time-courses are not simple and may have multiple peaks (Verduyn et al., 2009). Such circumstances would certainly impact the duration and may simultaneously impact the rise-time or intensity parameters. The time course of any emotional response can be described by the convolution of these three parameters.

3.1.2 Neural, Peripheral, Subjective, and Behavioral Indicators of Emotion

In order to describe neural mechanisms that underlie the three temporal features defined by affective chronometry, it is first necessary to introduce the dynamic signals that comprise an emotional response. These signals include neural activity, peripheral physiology, subjective 'feelings', and objective behavior. We briefly describe each of these below.

Neural signals. A variety of neural mechanisms support emotional responses in animals and humans. We briefly review the methods used to measure neural signals described here.

In animals, neural measures can quantify electrophysiological activity through extra- and intra-cellular recordings. Extracellular recordings can be acquired from either single or multi-site electrodes using high spatiotemporal sampling. These measure the local field potential (LFP), or the summed electrical changes occurring near the electrodes (Buzsáki et al., 2012; Csicsvari et al., 2003). As these electrodes measure activity across many neurons, high frequency 'spikes' in the local field primarily reflect synchronous neuronal firing. In contrast, intracellular electrodes record electrical activity within a single cell providing richer information about the mechanisms of activity spikes, including cellular inputs, intrinsic cellular properties, and subthreshold activity (Henze et al., 2000). These measurements capture rich temporal information on a timescale of milliseconds.

Experimental manipulations of neural circuits can further establish causal links between brain and behavior. One method in animals involves the direct manipulation of neuronal activity via optogenetics. Optogenetics involves the engineering of cells to be excited or inhibited by specific frequencies of light (for a review see Fenno et al., 2011). This method allows for manipulation of neural activation or silencing across timescales (Guru et al., 2015). These manipulations allow scientists to causally connect neural dynamics across milliseconds and seconds directly to behavior.

Compared with animal research, measures of neural activity in humans are often more indirect and less precise, in part because they tend to be less invasive. Electrophysiological activity can be measured by placing electrodes on the scalp, using electroencephalography (EEG) or magnetoencephalography (MEG).These methods record cortical electrical brain activity with high temporal resolution. However, the source of the electrical changes are challenging to identify, particularly if the source comes from deeper brain regions, such as the amygdala (Buzsáki et al., 2012; Darvas et al., 2004; Hansen et al., 2010). Moreover, EEG signals represent the electrical potential across large neuronal populations of co-active, similarly oriented pyramidal cells in the cortex (Kirschstein & Köhling, 2009). Thus, the spatial resolution of EEG is limited relative to single-unit and LFP recordings.

Relative to EEG and MEG, functional magnetic resonance imaging (fMRI) provides superior spatial resolution by imaging the whole brain. Using magnetic field gradients, fMRI locates changes in oxygenated blood flow throughout the brain. Blood flow is thought to reflect metabolic responses to increased neuronal activity (Poldrack et al., 2011), but the temporal resolution is less precise than EEG or MEG.

Peripheral physiological signals. There are several peripheral physiological responses that occur in response to affective events. Triggered by the central nervous system, these peripheral indicators reflect sympathetic responses to affective stimuli (Bradley & Lang, 2000). For example, pupillary dilation and constriction are modulated following affective stimuli (Maffei & Angrilli, 2019). Changes in heart rate and heart rate variability are also linked to emotional responses (Mauss & Robinson, 2009). Similarly, the Galvanic Skin Response (GSR) measures sweat excretion in response to arousing stimuli (Lang et al., 1993; Mauss & Robinson, 2009) as does respiration rate (Homma & Masaoka, 2008). Emotional responses can also be measured via facial electromyography (EMG), an objective measure of facial muscle activity. Emotional expressions, such as frowning and smiling, evoke EMG activity which track the valence and intensity of affective reactions (Cacioppo et al., 1986).

Subjective emotional signals. Perhaps the most obvious indicators of an emotional episode arise from an individual's description of the feelings comprising the experience. Subjective descriptions of emotion can be obtained retrospectively or during the emotional episode. This is typically accomplished with laboratory-based self-report surveys or via experience sampling methods (Shiffman et al., 2008). Subjective reports of emotional episodes are often structured with questions that assess unique emotions, such as "fear," "happiness," or "frustration." Alternatively, self-report instruments may ask an individual to average across core dimensions of their emotional experience such as valence (i.e., positive vs negative) and arousal (i.e., high vs. low) of an emotion (Russell, 1980).

Behavioral signals. Behavioral responses to stimuli can yield insight into an organism's central emotional state. Using observable behavior as a proxy for emotional state enables researchers to infer the neural mechanisms driving affective behaviors across species.

Across species, objective behavioral states such as feeding, grooming, and freezing can be viewed as expressions of "emotion primitives" (Panksepp, 2004). The neural mechanisms that subserve these affective behaviors in lower organisms are conserved through evolution and can be construed as the "building blocks" for human emotional responding (Anderson & Adolphs, 2014). For example, similar neural mechanisms that drive rodent freezing responses to aversive stimuli support the emergence of fearful "feeling states" in humans. Some theorize that affective behaviors emerge from such central emotional states (Anderson & Adolphs, 2014).

Such a viewpoint allows researchers to infer the valence and dynamics of the underlying emotional state from the type and timing of behavioral responses.

Aversive emotional states can be inferred from a variety of animal behaviors across phyla. Behaviors that involve avoidance of a threatening stimulus or situation, such as freezing, hiding, or fleeing a threat, are generally thought to indicate aversive emotional states. For instance, in organisms as simple as the roundworm *C. elegans*, an aversive state can be inferred from stereotyped escape behaviors (Cermak et al., 2020; Leung et al., 2016). In rodents, compulsive self-grooming in response to an aversive stimulus may indicate an anxious emotional response, akin to human self-soothing responses to stress (Spruijt et al., 1992).

Aversive emotional states may also be inferred from the timing of behaviors. In humans, faster reaction times to aversive stimuli may indicate that an individual's response was primed by a latent aversive emotional state (Neta & Tong, 2016). Similarly, in non-human species, the affective structure of an organism's environment can be inferred from the amount of time that the organism spends pausing in place before making a behavioral choice (Redish, 2016). Additionally, some objective behaviors can also be used as proxies for appetitive states. For example, active mating and feeding behavior indicate that an animal has appraised their environment as sufficiently safe to exploit potentially rewarding opportunities (McNaughton & Corr, 2018).

3.1.3 Interim Summary

In the remaining sections we describe how neural circuits supporting emotion give rise to the rise-time, amplitude, and duration of emotion. As mentioned above, these emotional dynamic parameters are interrelated as are the neurobiological process that underlie them As such, established neural circuits involved in emotional responses, including the midbrain (periaqueductal grey [PAG]), sensory regions, thalamus, amygdala, bed nucleus of the stria terminalis (BNST), nucleus accumbens (NAcc) and the striatum, hippocampus, the orbitofrontal cortex (OFC), and the medial prefrontal cortex (mPFC) among others, contribute to the temporal features of affect. Below, we draw from both animal and human research to highlight the circuits relevant to each parameter of emotional dynamics and describe stimulus and contextual properties that modulate these parameters.

3.2 Parameter 1: Rise-Time

Conceptually, rise-time refers to the time that it takes an affective response to reach its peak following stimulus onset (Davidson, 1998). Here, an affective signal is some measured output of a response system, for example a subjective feeling, a psychophysiological process, or measured neural activity. The rise-time of an emotional response relies on multiple information processing components, including stimulus detection, reorienting, attentional allocation, and stimulus valuation. The neural systems involved in these processes, and how they may contribute to the affective rise-time described below.

3.2.1 Critical Circuits

The proposed neural systems subserving affective rise-time necessarily involve cortical sensory regions, which detect salient, goal-relevant stimuli. Faster detection of, and orienting to, a stimulus can hasten the rise-time of an affective response to that stimulus. This sensory information originates from the specialized cortical regions (i.e. occipital, auditory cortices) and then flows through modality-specific cascades toward higher association regions (McDonald, 1998; Mesulam, 1998) including the frontal, insular, parietal, and temporal cortices. These association regions not only receive information via this cortical cascade, but they also have bidirectional connections with the thalamus and amygdala (McDonald, 1998).

While the amygdala is not only relevant for affective rise-time, the basolateral amygdala (BLA) is well-positioned to influence rise time as it receives sensory cues, imbues them with value, and propagates this information to downstream regions. Neurons in the BLA, which includes the lateral and basal nuclei (Sah et al., 2003), drive emotional learning, demonstrated through threat and reward conditioning paradigms (Quirk et al., 1995; Johansen et al., 2010; Namburi et al., 2015), and from studies lesioning the lateral amygdala (LeDoux et al., 1990; Klumpers et al., 2015).BLA neurons differentially encode fear and reward associations (Beyeler et al., 2018; Paton et al., 2006), which engage separate downstream pathways. BLA neurons encoding reward associations propagate signals to the NAcc, which drives reward-seeking behavior (Stuber et al., 2011). In contrast, neurons encoding aversive associations propagate signals to the central nucleus of the amygdala (CeA; Namburi et al., 2015) and the neighboring BNST (Fox & Shackman, 2019; Kim et al., 2013). When BLA neurons signal an aversive conditioned auditory stimulus to the CeA, a subset of lateral CeA neurons become excited while a separate subset becomes inhibited (Ciocchi et al., 2010). These inhibited neurons in turn disinhibit medial CeA neurons, which signal threat-conditioned action (Fadok et al., 2018). Relatedly, BLA projections to the BNST also promote emotional behaviors (Davis et al., 2010; Fox & Shackman, 2019). These findings highlight the importance of BLA connections with other regions to translate information regarding stimulus value into motivated behavioral responses.

The speed of signaling in these circuits could impact the time it takes an affective signal to peak. For example, Tye et al. (2008) conducted a reward conditioning experiment in rodents and found that greater task efficiency, defined as the number of rewards earned divided by the number of cues, was linked to a higher proportion of cue-responsive amygdala neurons and stronger amygdala-thalamus connections. Other work has shown that stimulus valence alters glutamatergic synaptic strength of BLA efferents, such that BLA-CeA synapses are weakened during reward conditioning and BLA-NAcc synapses are weakened during fear conditioning (Namburi et al., 2015). More research is needed to pinpoint exactly how these neural metrics of efficiency relate to the rise-time or onset of affective behavior.

Affective rise-time may also be determined, in part, by the mPFC, where information from the BLA, the hippocampus, and other subcortical and cortical regions converge. Using contextual information, the mPFC can modify the expectedness and value of a stimulus based on the appropriateness of the stimulus and context for the organism's current state and environment (Grace & Rosenkranz, 2002; Calhoon & Tye, 2015). This may also impact affective rise-time. For example, Mattavelli et al. (2011) measured response time when classifying happy and angry faces following a congruent or incongruent priming cue (i.e. the word happy or angry). They found that during congruent trials, when subjects were contextually primed, response times were longer when a transcranial magnetic stimulation pulse disrupted the mPFC (Mattavelli et al., 2011). This suggests that the mPFC can streamline affective responses based on the environmental cues and context.

Beyond any singular region, the coordination and synchrony of neural activity between the mPFC, amygdala, and hippocampus during affective processing facilitates information transfer and thus the affective rise-time (Buzsáki et al., 2012; Pape et al., 2005; Paz et al., 2008; Seidenbecher et al., 2003). With regards to affective responding, synchrony between the hippocampus and the BLA is increased in response to the conditioned stimulus after threat conditioning (Seidenbecher et al., 2003). Moreover, mPFC-originating theta rhythms can also promote safety behaviors after extinction (Lesting et al., 2013). Specific to affective rise-time, Karalis et al. (2016) demonstrated that prefrontal-amygdala synchrony predicted the speed of freezing behavior of rodents during threat conditioning. These studies demonstrate that dynamic shifts in oscillatory synchrony among regions shape the unfolding of emotion states.

3.2.2 Modulators: What Influences Rise-Time?

There are a number of stimulus and contextual properties that can influence neural circuits involved in emotion and also the affective rise-time. We posit that rise-time is likely to be faster for stimuli that are emotionally congruent, salient, and unambiguous. Importantly, these features may correlate differently with one another across contexts. For example, stimuli that are salient may be unexpected or incongruent. Therefore, while we discuss the literature that supports these modulators of rise-time, we acknowledge that more work is needed to determine when, how, and for whom these modulators are prioritized.

Congruence. Emotional rise-time is faster for emotionally highly congruent material (John et al., 2016; Dzafic et al., 2019). As a predictive organ, the brain is constantly forming expectations about what is likely to occur (Clark, 2013). As such, it is often functionally adaptive and efficient to bias the appraisal of stimuli as threatening in aversive contexts, or conversely, to prioritize the appraisal of stimuli as rewarding in appetitive contexts. Prioritizing congruent information, which streamlines affective rise-time, can be achieved through the biasing of sensory systems (Pourtois et al., 2013). This biasing is supported, in part, by amygdala influence on gating mechanisms in the thalamus (John et al., 2016).

The amygdala can bias attention toward emotionally relevant information in the environment through its connection with the thalamus. While the amygdala receives projections from the thalamus, it also exerts excitatory projections back to the thalamic reticular nucleus (TRN), which inhibits the other thalamic nuclei (Pinault, 2004). Specifically, the TRN exerts inhibitory control over the sensory thalamus, which promotes competitive gating of thalamo-cortical signals. The TRN is considered a hub of the attentional system (McAlonan et al., 2006) and this amygdala-TRN connection suggests that emotionally-relevant information can influence ongoing attentional and sensory processing (John et al., 2016). Excitatory amygdala projections to the TRN can directly influence this attentional controller, biasing attention toward emotionally relevant information and suppressing competing sensory signals (John et al., 2016). Tuning attention to emotionally relevant and congruent sensory information can speed the rise-time of emotional responses.

One demonstration of the modulation of rise-time by congruence in humans comes from a structural and functional MRI study employing a dynamic emotion perception task (Dzafic et al., 2019). Similar to any Stroop effect, participants classified video clips as happy or angry, each of which was preceded with a “happy” or “angry” cue containing a still-image and the corresponding emotion word. These cues were either congruent or incongruent with the subsequent video (Dzafic et al., 2019). During congruent trials, a faster behavioral response time to angry stimuli was associated with greater recruitment and connectivity within an amygdala-limbic functional network. This network consisted of the right amygdala, hippocampus, mammillary bodies, caudate, and subgenual anterior cingulate cortex (Dzafic et al., 2019). This finding supports the amygdala as a key for affective rise-time and emotional-congruence as a modulator that can hasten rise-time, including the speed of behavioral responses.

Salience Rise-time is likely faster for perceptually salient information. Salient stimuli are often prioritized, therefore shortening the rise-time for affective responses. In the visual system, salient stimuli are those that “appear to an observer to stand out relative to their neighboring parts” (p. 185, Borji & Itti, 2010). These “stand-out” stimuli or features can be conceptualized as spatial or temporal prediction errors—deviations from what is anticipated. This definition of salience stands in contrast to the argument that stimulus “congruency” facilitates rise-time. However, it may be that either congruency or incongruency (salience) promotes affective rise-time, but that the direction of the modulation depends on context and the extent of the congruency or incongruency.

Many visual salience models account for the rapidity of attention and orienting by analyzing populations of neurons in the visual cortex. According to some models, these “stand-out” stimuli are encoded in various maps specific to perceptual features, such as luminance contrast, edges, color, and motion (Borji & Itti, 2010;

Itti et al., 1998). Other models of saliency maps suggest that multiple feature maps are not required, but rather, firing rates across V1 neurons, regardless of feature tuning, yield a single saliency map (Li, 2002). Still other models focus on subcortical structures that may encode salience, such as the superior colliculus (White et al., 2017). According to most of these computational models, bottom-up visual saliency maps interact with top-down priority maps, perhaps emanating from medial prefrontal cortical regions, to encode the behavioral relevance of stimuli, to guide attention and behavior (Fecteau & Munoz, 2006; Tanner & Itti, 2019).

Emotional faces are one example of salient stimuli that modulate the neural processes underlying affective rise-time in humans. In support of this, humans exhibit faster detection of emotional faces, particularly angry faces, compared with neutral faces (Öhman et al., 2010). For decades, affective neuroscientists have proposed that fast threat detection is possible through a "fast path" or "low road" route to the amygdala that bypasses cortical regions (Garrido et al., 2012; LeDoux, 1996). Through the fast path, the amygdala receives sensory information subcortically through the pulvinar nucleus of the thalamus, prior to reaching the sensory cortex (LeDoux, 1996; Méndez-Bértolo et al., 2016; Morris et al., 1999). From an evolutionary perspective, this fast path exists to prioritize responding to salient survival-related stimuli.

Recent evidence in humans further indicates that emotional faces may be sufficiently salient to reach the amygdala through this fast path (McFadyen, 2019; McFadyen et al., 2017; Méndez-Bértolo et al., 2016). Specifically, an intracranial electrophysiological study demonstrated that low spatial frequency fearful faces, which appear as blurred versions of the normal faces that maintain the original brightness and contrast, elicited amygdala activity approximately ~100 ms faster than in ventral visual cortex (Méndez-Bértolo et al., 2016). However, additional MEG work has demonstrated that the fast path amygdala responses may extended to faces regardless of spatial frequency or emotional expression (McFadyen et al., 2017). Additional work exploring which types of stimuli and information are prioritized in this fast path will help inform salient features that may modulate affective rise-time.

Ambiguity Rise-time is faster for non-ambiguous stimuli (Neta et al., 2009). Features of emotionally ambiguous stimuli, (i.e., a surprised facial expression or a woman crying in a wedding dress) convey subtle, inconclusive, or even conflicting information regarding valence. Such stimuli may be open to multiple interpretations and may require additional contextual information to be appraised. In contrast to controlled experiments that employ clearly-valenced and unequivocal stimuli, real-world affective events can be ambiguous. More elaborated and prolonged processing is required to resolve ambiguity and determine stimulus value.

Resolving ambiguity requires PFC and other cortical input to integrate additional contextual information (Bublatzky et al., 2020; Stujenske et al., 2020). Using MEG In humans, Bublatzky et al. presented morphed, difficult-to-recognize emotional faces during both contextual threat and safety. When subjects classified ambiguous fearful expressions under contextual threat or when subjects classified ambiguous happy faces under contextual safety, there was an amplification of early activity in centro-parietal (between 63–127 ms) and prefrontal regions (between 103–157 ms; Bublatzky et al., 2020). This double dissociation highlights the role of cortical regions in contextualizing and evaluating nuanced, ambiguous stimuli. This example also reiterates the influence of context on stimulus appraisal, as ambiguous stimuli are more likely to be appraised in congruence with the context.

Another way that the cortical regions in general, and the mPFC in particular, help resolve ambiguity is through fear generalization. Fear generalization requires that organisms determine whether unconditioned stimuli that are similar to, yet distinct from, conditioned fear stimuli nonetheless represent threat (Asok et al., 2019). In mice, stimulating prelimbic cortical (analogous to mPFC in humans) inputs to the BLA enhances discrimination between stimuli, meaning that the mice *did not* generalize fearful responses to non-threatening stimuli (Stujenske et al., 2020). Overall, cortex-dependent processing and contextualizing that resolves ambiguity could, in turn, modulate affective rise-time in response to emotionally ambiguous stimuli.

3.3 Parameter 2: Intensity

Conceptually, the intensity of an emotional response refers to the absolute value of magnitude of that response (Davidson, 1998). Terms such as the "amplitude" (Russell, 1980) or "scalability" (Anderson & Adolphs, 2014) of an emotion share conceptual overlap with our use of the term intensity. Importantly, while an emotion's intensity is often considered to vary continuously (e.g., from low to high intensity), the behavioral outputs associated with increasing intensity need not increase monotonically. For instance, under increasingly proximal threats, rodent behavior shifts from passive observation, to freezing, to attack ("circa-strike;" Blanchard et al., 1990). These qualitative shifts in behavior depend on quantitative shifts in stimulus proximity, and in all likelihood, increases in affective intensity. Moreover, such increases in an emotion's intensity are impacted by its rise-time and can subsequently influence its duration.

3.3.1 Critical Circuits

The neural circuits involved in an emotion's intensity are deeply intertwined with those influencing its rise-time and duration. The intensity of an emotional response can be modulated via activity in brain-stem, subcortical/limbic, as well as cortical regions. Panksepp and others have argued that low-levels of stimulation of the most evolutionarily old and conserved brain regions, including the periaqueductal gray (PAG) of the midbrain, causes robust, reliable, and specific emotional responses (Panksepp, 2004). One reason for this assertion is that the level of electrical stimulation needed to cause affective reactions is far lower and far more specific in the evolutionarily old midbrain than in regions that emerged more recently in phylogeny (even compared to the amygdala and nucleus accumbens, let alone the cerebral cortex). Furthermore, stimulation of the midbrain subnuclei appears to cause affective reactions regardless of context. Critically, the magnitude of stimulation scales with the intensity of affective reaction.

However, evolutionarily old brain regions, such as the PAG, do not alone drive an emotion's intensity. More recently evolved associative learning structures, including the amygdala, hippocampus, NAcc, ventral pallidum, in addition to the association cortex (Mesulam, 1998) share structural connectivity. These regions encode and represent the life-history of the organism and provide the essential context about what to expect and how to make sense of incoming information. The interaction between these regions determines the intensity of the emotional response and appropriate behavioral output. For instance, recent fMRI work using machine learning indicates that increasing subjective ratings of negative emotion in response to affective images are predicted by a specific pattern of cortical and subcortical brain responses (Chang et al., 2015). These regions included amygdala, insula, PAG, and posterior cingulate cortex, among others. Critically, there is no single region or circuit necessary or sufficient for predicting the intensity of emotional experience, indicating that intensity is encoded in this circuit. In work that simultaneously acquires fMRI and objective facial EMG from the corrugator ('frowning' muscle) during a similar picture viewing task, both lower vmPFC activity and higher amygdala activity predicted higher intensity of corrugator activity (Heller et al., 2014). As further evidence that no single region produces aversive emotions, a recent intracranial stimulation study of the human amygdala finds limited specificity for driving emotional responses (Inman et al., 2020).

Intensity of hedonic processing also depends on a distributed circuit including cortical and subcortical regions. Human neuroimaging studies report that the OFC and insula encode the pleasantness of foods (Kringelbach et al., 2012; Small et al., 2001). For example, cortical activity robustly tracks the pleasantness of food and the intensity of this pleasure and the concomitant cortical activity decline as individuals become satiated (Kringelbach & Rolls, 2004). This evidence is supported by complementary neuroeconomic decision-making work indicating that the value of a stimulus is encoded in a variety of cortical (mPFC/OFC) and subcortical (NAcc) regions (Knutson & Cooper, 2005).

3.3.2 Modulators: What Influences intensity?

Stimulus Proximity As noted above, the proximity of an affective stimulus strongly modulates the intensity of the emotional reaction and the accompanying behavior. Fanselow and Lester advanced the "Threat Imminence Continuum" model (Fanselow & Lester, 1988) of shifts in behavior based primarily on studies in rodents. This model posits that threat-states change depending on the proximity of the threat (undetected, detected but far away, or close enough to immediately attack). Mobbs and others have applied this framework to create an fMRI paradigm where the subject actively evades an artificial predator that can chase, capture and shock the subject. Mobbs and colleagues showed that as an artificial predator came closer to the subject, activity shifted from primarily cortical (e.g., vmPFC) to midbrain (PAG) regions (Mobbs et al., 2007). Mobbs has replicated and extended this work using more realistic stimuli (Mobbs et al., 2010). For instance, when a tarantula was placed progressively closer to the subject's foot, they found that closeness was associated with greater activity in the PAG, amygdala, and BNST. Conversely, distance was associated with greater OFC activity. Pessoa and colleagues have used a similar paradigm of increasing threat proximity and found that threat proximity is similarly related to amygdala and salience network activity (Meyer et al., 2019). Together, these studies suggest that higher forebrain areas are involved in slower, deliberate responses to distant or potential threats, whereas the midbrain and perhaps the amygdala mediate fast, "hard-wired," defensive reactions to imminent danger (Mobbs & Kim, 2015).

Stimulus Repetition The repeated presentation of identical or similar stimuli (i.e., sharing several perceptual or categorical properties) leads to habituation (Thompson, 2009). This is a process by which the amplitude of an emotional response becomes attenuated. Neuronal habituation to repeated presentation of similar stimuli occurs throughout the brain, from the brainstem up to the cortex. The rate of habituation is typically a negative exponential function of the number of stimulus presentations. Habituation occurs in almost all readouts of emotion, including physiology (Davis, 1934), facial reactivity (e.g., startle: Prosser & Hunter, 1936), and exploration of novel contexts (Welker, 1961)). Habituation is a type of short-term memory and indicates that more novel stimuli (i.e., stimuli of uncertain value) can often evoke stronger affective reactions than recently encountered stimuli of known value. Moreover, the capacity for stimulus adaptation (i.e., habituation) is present throughout the brain—brainstem regions drive core emotional responses (not necessarily subjective human 'feelings'), as well as evolutionarily newer regions (Sokolov, 1963). Such a conceptual orientation is central to more modern theories of "the predictive brain" (e.g., Friston et al., 2009).

Neurochemical modulators of hedonic processing Rodent models of hedonic processing provide insights into the circuits and neurochemical systems influencing emotional intensity. Berridge and his colleagues have mapped the neural circuits involved in hedonic processing (Berridge & Kringelbach, 2015). In particular they have identified distinguishable neural processes underlying the incentive salience ('wanting') and hedonic ('liking') processing of rewards. Moreover, their work has linked neuronal mechanisms of hedonic processing with objective affective behaviors during ingestion of pleasant stimuli. These objective reward-related behaviors, including lip licking and tongue protrusions, are readily observable in rodents, nonhuman primates, and human infants alike.

Neurochemical signals in subcortical regions modulate the intensity of these objective affective behaviors in rodents (Berridge, 2019). Stimulation of opioid, orexin, and endocannabinoid systems within either the NAcc shell or the ventral pallidum increase the frequency of objective liking behaviors. This suggests that enhanced signaling in these systems may increase the intensity of the subjective emotional hedonic experience (Berridge, 2019; Smith et al., 2011). Additionally, these effects appear to be specific to opioid, orexin and endocannabinoid systems, as dopamine agonist microinjections into the same regions did not similarly modulate hedonic responses (Castro & Berridge, 2014).

Moreover, the NAcc and ventral pallidum receive input from cortical sites, notably the prefrontal cortex and insula, which can also amplify hedonic reactions. To that end, Castro and Berridge extended earlier findings by injecting the mu-opioid agonist DAMGO and neuropeptide orexin into orbitofrontal and insular regions to map their effects on the intensity of hedonic responses. In small (6–8 mm^3) hedonic hotspots in the anterior OFC and posterior insula, they found that mu-opioid or orexin microinjections amplified the hedonic impact of sweetness, expressed as a nearly 300% increase in behavioral "liking" reactions to the sucrose taste. Further supporting the role of these cortical regions in amplifying hedonic processing, stimulation of both the anterior OFC and posterior insula increased activity throughout the broader hedonic circuit, including in the NAcc and ventral pallidum (Castro & Berridge, 2017). These data suggest that there exist specific neurochemical modulators of the intensity of emotional responding within specific neuronal circuits supporting affective processing.

3.4 Parameter 3: Duration

Conceptually, the duration of an emotional response refers to the time that elapses between the start and end of the response. Here, the end of an emotional response is defined by an individual's return to a baseline state, or to the internal state that preceded the onset of the emotion. An enduring emotion may similarly be construed as a lasting perturbation. Enduring emotional responses are marked by lasting shifts in physiology, behavior, and cognition. Thus, the duration of an emotional response can be inferred via the duration of objective physiological and behavioral states in addition to subjective self-report.

3.4.1 Critical Circuits

After an emotional response begins, its duration depends on the persistence of activity in the underlying neural circuitry. This applies to all domains of emotional responses, including physiological, behavioral, and cognitive states (Major & Tank, 2004). In the sections that follow, we describe (1) how neuromodulators drive enduring emotional responses by sustaining neural activity in emotion-encoding circuits, (2) how persistent patterns of emotion-related network activity contribute to the duration of emotional responses, and (3) how evolutionarily conserved subcortical circuits that support the selection and maintenance of behavioral states also influence the duration of emotional states.

Role of neuromodulation in maintenance of persistent states Emotional states emerge and persist through the action of a subfamily of neurotransmitters known as neuromodulators (dopamine, serotonin, acetylcholine, and norepinephrine; Fellous, 1999). Neuromodulators originate in small brainstem nuclei that project broadly to cortical and subcortical regions. Via these diverse projections, neuromodulators enable global shifts in neural activity. In contrast to the fast and transient action of the excitatory and inhibitory neurotransmitters (glutamate and GABA), neuromodulators induce persistent brain and behavioral states (Flavell et al., 2013; Lee & Dan, 2012). Neuromodulatory activity enables organisms to adjust their behavior in response to dynamic environments and changing homeostatic needs (Pool & Scott, 2014).

The persistence of neuromodulatory activity appears to play a phylogenetically conserved role in the dynamics of internal emotional states. As threats and rewards manifest or an organism's needs change, neuromodulators fundamentally reconfigure neural circuits and their outputs (Marder, 2012). Through these context-dependent actions, neuromodulators enable flexible shifts in organisms' behavioral state. Critically, the duration of these states is determined in part by the rate at which neuromodulators are cleared from neuronal synapses (Gibson et al., 2015). In humans, drugs that regulate the concentration and efficacy of neuromodulators at the synapse are widely prescribed to treat psychiatric disorders such as depression, OCD, anxiety, ADHD, and psychotic disorders. Interestingly, the pathology of each of these disorders involves persistence of some internal state; be it an affective state in depression, a behavioral state in ADHD, or a cognitive state in psychosis.

Studies employing simple organisms with well-characterized neuronal connectomes clearly demonstrate that neuromodulators control the duration of persistent states that may be considered 'affective' (Lee & Dan, 2012). For example, in *C. elegans*, two neurochemicals (serotonin and pigment-dispersing factor) recruit neurons into opposing, bi-stable networks. These opposing networks drive opposing behaviors, such as roaming and dwelling (Ji et al., 2020). Similarly in *C. elegans,* dopamine exhibits dissociable, state-dependent effects on the duration of egg-laying behavior (Cermak et al., 2020). In larval zebrafish, dopaminergic activity reduces the susceptibility of persistent neural states to potential distractors by increasing the gain (i.e., relative strength) of relevant neural signals (Randlett et al., 2019). These examples demonstrate that neuromodulatory signaling enables an internal state (i.e., a response) to persist for as long as the stimulus that evoked it remains salient (Likhtik & Johansen, 2019).

One particular neuromodulator, dopamine, influences the duration of internal emotional states by, (1) reducing a state's susceptibility to distractors (Jacob et al., 2016), and (2) increasing the signal-to-noise ratio of stimulus representations in neural activity (Vander Weele et al., 2018). Dopamine influences behavioral impulsivity and the persistence of internal states through its effects on dopamine receptor-expressing neurons in the striatum—a region involved in the selection and maintenance of behavioral states (Graybiel, 1998). Specifically, dopaminergic activity modulates the stability of neuronal UP and DOWN states (Gruber et al., 2006), which refer to shifts in the thresholds at which neuronal hyperpolarization and depolarization occur (Major & Tank, 2004). Through these shifts in conductance thresholds, neuromodulators confer striatal UP and DOWN states with reduced susceptibility to distractors (Gruber et al., 2006). Thus, in motivationally relevant contexts, dopamine-mediated activity in striatal medium spiny neurons enables representations of salient information to persist in downstream cortical targets (this corticostriatal gating mechanism is described in greater detail below). In line with dopamine-mediated neural persistence, a paucity of D2 and D3 dopamine receptors in the ventral striatum is associated with increased impulsive behavior in rodents (Barlow et al., 2018). Moreover, in humans, reduced structural coherence of dopaminergic projections from the ventral tegmental area to the ventral striatum predict greater impulsivity, and thus impaired behavioral persistence (MacNiven et al., 2020). Impulsive behavior may indicate impaired persistence in neural activity perhaps due to increased susceptibility to distractors (Barlow et al., 2018).

In addition to dopamine, serotonin also modulates the duration of emotional states. This is accomplished via the effects of serotonin on circuits involved in action selection. To illustrate, in zebrafish, inescapable aversive behavioral challenges elicit enduring states of neural activity in the ventral habenula. Inhibitory projections from the ventral habenula then suppress downstream serotonergic neurons in the dorsal raphe nucleus. The resulting reduction in global serotonergic signaling prompts a shift in the organism's behavioral state, from an active to a sustained passive coping strategy. This is consistent with learned helplessness behavior in animal models of depression. Here, the shift to a passive behavioral state is supported by the phylogenetically conserved, inhibitory effect of serotonin on excitatory projections from the basal ganglia to the habenula (Shabel et al., 2012). Via these projections, reduced serotonergic activity and resultant habenula hyperactivity increase the signal-to-noise ratio of the aversive stimulus representation, which ultimately generates an enduring, passive behavioral state (Andalman et al., 2019).

Role of persistent activity in Amygdala**—HPC—mPFC network in emotion duration** Across species, the duration of an emotional or behavioral state is also linked to the persistence of neural activity in emotion-encoding subcortical regions such as the amygdala (Kennedy et al., 2020). For instance, enduring emotions, such as anxiety, are thought to be supported by enduring neural signals in emotion-encoding regions such as the amygdala and BNST (Lee et al., 2017; Waugh et al., 2015). Conversely, transient emotional states of the same valence, such as fear, are generated by short-lived signals in the same regions (Lee et al., 2017). Human fMRI studies have revealed a similar relationship between the duration of subjective emotion and the duration of neural signals in emotion-encoding regions such as the amygdala, thalamus, and midbrain (Waugh et al., 2016). However, the duration of emotional responses is not only determined by these subcortical structures, but also by synchrony within a frontolimbic network comprised of the amygdala, hippocampus, and mPFC.

Oscillatory synchronization between the amygdala and connected regions contributes to the duration of emotional states. One particularly important region in this network is the mPFC, which maintains neural representations of affective stimuli even after they dissipate (Bliss-Moreau & Rudebeck, 2021; Powell & Ginsberg, 2005). Moreover, persistent oscillatory entrainment between the mPFC, amygdala, and hippocampus support enduring freezing responses to conditioned fear stimuli in rodents (Seidenbecher et al., 2003). In particular, the duration and power of 4 Hz oscillatory synchronization between the mPFC and BLA predicts the duration of freezing behavior in rodents when exposed to aversive conditioned stimuli (Karalis et al., 2016). Even after stimuli are no longer present, enduring stimulus representations in the mPFC are transmitted to the BLA to produce these behavioral responses. In related rodent threat-conditioning paradigms, fear memory retrieval and behavioral responses are supported by phase-correlated interactions between mPFC neurons and the BLA (Bocchio et al., 2017). However, the functional role of oscillatory entrainment extends beyond fear conditioning. For example, entrainment within this circuit further transmits state-dependent contextual information to the striatum during behavioral decision-making. As detailed below, this information biases the duration of emotional states (Sharpe et al., 2019).

Role of Cortico-striatal-thalamo-cortical circuitry in neural states and state transitions An emerging literature posits that corticostriatal circuitry involved in motor planning and action selection (Gurney et al., 2015; Redgrave et al., 2011) maintain persistent behavioral, cognitive, and emotional states (Awh & Vogel, 2008; McNab & Klingberg, 2008; O'Reilly & Frank, 2006). This cortico-striatal-thalamo-cortical (CSTC) circuit receives multiple sources of information from the cortex and gates relevant neural signals into behavior. This is accomplished via the CSTC circuit's recurrent, closed loop architecture. In this circuit, multiple sources of information are routed from distinct cortical regions to the basal ganglia, through the thalamus, and back to the cortex (Alexander et al., 1986). The CSTC circuit's primary mechanism of action is inhibitory, serving to gate simultaneously competing cortical inputs (e.g., competing motor programs) into stable behavioral outputs (e.g., motor actions). Specifically, when a behavioral state is no longer adaptive for an organism, the basal ganglia shift the behavioral state by inhibiting its current output while simultaneously releasing a more optimal behavior from inhibition. Similarly, the basal ganglia may also hierarchically control the input, output, and maintenance of information in frontal cortical regions involved in higher-level cognition and planning (Chatham & Badre, 2015). Thus, the basal ganglia ultimately arbitrate the duration of an organism's behavioral or cognitive state depending on a state's current value to the organism's survival.

CSTC circuit loops and the values encoded in their inputs ultimately govern whether internal states persist or are interrupted by competing signals. Indeed, the duration of behavioral states depends on an organism's current goals (Hubbard et al., 2020) and the relative values of its behavioral options in the current state (Daw et al., 2006). These values, which dictate the duration of behavioral, cognitive, and emotional responses, are encoded in cortico-striatal projections from the OFC, the ventromedial prefrontal cortex (vmPFC), and the dorsolateral prefrontal cortex (dlPFC) to the striatum (Sharpe et al., 2019). Within these cortical regions, distinct neural mechanisms convey value signals to the striatum. These value signals in turn govern the duration of behavioral states. For example, the OFC transmits value judgments through its projections to cholinergic interneurons in the striatum (Wilson et al., 2014). Additionally, context and salience-encoding limbic inputs to prefrontal and striatal regions influence behavioral state durations (Barlow et al., 2018; see "*Subcortical regions…*" in Sect. 3.4.2). In summary, functionally diverse inputs to the striatum encode the salience of sensory information and the relative value of simultaneously competing cognitive and behavioral states. Ultimately, these values govern the duration of emotional states through inputs to CSTC loops.

3.4.2 Modulators: What Influences Duration?

Intensity of the stimulus or emotional response The duration of an emotional response depends in part on the amplitude of the emotional response (Waugh et al., 2010). First, the intensity of an initial emotional reaction predicts its duration in subjective reports of emotional experience (Frijda et al., 1991). Objective assays of animal behavior replicate this effect. For example, in *Drosophila*, the intensity of a threatening stimulus predicts a more persistent behavioral response (Gibson et al., 2015). In this case, one or more neurons in the model organism cumulatively integrate signals from sensory neurons that encode the threatening stimulus. As time passes, accumulating sensory information in these so-called "leaky integrator" neurons decays at a constant rate. Thus, in circumstances where an organism faces repeated or high-amplitude sensory inputs, the accumulation of sensory information can outpace the decay rate. Within leaky integrator neurons, asymmetry in the rates of signal accumulation versus signal decay yields persistent activity, which can allow a behavioral response to persist even after stimuli dissipate. Convergent evidence suggests that persistent integrator neuron activity is necessary and sufficient to drive enduring behavioral responses in *Drosophila* (Jung et al., 2020). In sum, the response characteristics of integrator neurons (i.e., accumulation and slow decay of sensory signals) translate intense and persistent stimuli into more potent and lasting behavioral outputs.

Subcortical regions influence emotion duration Neural activity in subcortical (i.e., limbic) regions influences the duration of emotional states via interactions with CSTC circuitry. Through their projections to CSTC circuits, limbic regions may initiate cortical state transitions or bias the probabilities of subsequent state shifts. As a result, limbic inputs to the CSTC circuitry may influence the persistence of neural and behavioral states that underlie emotional responding. This is accomplished in part through limbic influence over the striatal-substantia nigra-thalamo-cortical path (Aoki et al., 2019). Through this interaction, neuronal activity in limbic regions can unilaterally suppress thalamo-cortical output from the CSTC loop. This enables salient sensory inputs to perturb persistent states in CSTC-mediated neural activity. Functionally, this circuit may reduce the duration of an internal emotional state by terminating it altogether.

Bottom-up, neuromodulatory influence in the striatum can also bias the duration of behavioral states. In particular, aberrant dopaminergic signaling in CSTC circuits reduces the duration of behavioral states via impulsive behavioral responding. In both animal and human models, reduced density of D2 and D3 dopamine receptor subtypes seems to underlie natural variability behavioral impulsivity (Buckholtz et al., 2010). Here, as in earlier examples, dopaminergic activity affords behavioral states greater resistance to potential distractors. This influence of dopamine on behavior may be explained by either the intrinsic effects of dopamine on the action selection machinery in the basal ganglia, or by dopaminergic effects on the signal-to-noise ratio of projections to CSTC circuits originating in the amygdala and the OFC.

Top-down influences from limbic and frontal regions may also influence the duration of emotional states by biasing the probability of state transitions. Indeed, lesions in limbic and orbitofrontal regions of the brain yield changes in CSTC signaling and increases in impulsive behavior (Barlow et al., 2018; Mobini et al., 2002). Additionally, increased functional connectivity within limbic networks, and reduced connectivity between frontal networks both contribute to impulsive behavior (Barlow et al., 2018). However, it remains unclear whether these top-down effects are independent of the bottom-up neuromodulatory influences of dopamine in the striatum (Dalley & Robbins, 2017). Emerging evidence from rodents suggests that the amygdala may indeed play an explicit role in coding real-time changes in behavioral states. Indeed, distinct neuronal subpopulations in the BLA encode behavioral state transitions (e.g., exploring vs. freezing) through slow-oscillating, attractor-like dynamics (Gründemann et al., 2019). State encoding in the amygdala may serve to integrate affective information into thalamocortical state representations via its vast cortical and subcortical connections. While this mechanism requires further investigation, it represents one additional process through which subcortical regions might influence state duration.

Frontoamygdalar circuits **support the regulation of emotional states** The duration of an emotional response also depends on whether affectively salient stimuli are gated into conscious awareness (see Sect. 3.2). In conjunction with the mechanisms described by Mitchell and Greening (2012), persistent activity in frontal regions modulates amygdala activity (Inagaki et al., 2019), which gates sensory information in and out of conscious awareness. This is related to the well-established notion that frontoamygdalar connectivity supports the regulation, maintenance, and suppression of internal emotional states (Davidson, 2002). In another example of this phenomena, successful fear suppression is mediated via functional connectivity between the perigenual PFC and the amygdala, while unsuccessful suppression is marked by increased functional connectivity between the amygdala and regions in the ventral visual stream (Amting et al., 2010). This suggests that successful emotion regulation, which can shorten an emotional episode, is characterized in part by frontal influence over amygdala activity, and gating of information flow between the amygdala and sensory centers.

Conversely, inhibition of the lateral PFC (implicated in top-down control over emotional states) via transcranial magnetic stimulation increases the influence of affective information from previous experiences on future decision-making (Lapate et al., 2017). Here, a paucity of frontal control over emotion-encoding regions in the brain generates an emotional "spillover" effect that serves to lengthen the duration of aversive emotional states in the brain. Relatedly, the aforementioned study by Waugh et al. (2016) demonstrates that human emotions endure via persistent neural activity in key medial frontal, limbic, and midbrain regions; and effortful emotion regulation serves to shorten the persistence of activity within these regions. Finally, additional evidence from human fMRI studies suggests that dissociable projections from the ventrolateral PFC to the striatum and the amygdala mediate successes and failures in emotion regulation, respectively (Wager et al., 2008). Taken together, these findings suggest that the persistence of activity between prefrontal regions and emotion-encoding regions mediates the duration of emotional states.

3.5 Conclusion

Here, we have highlighted several neural mechanisms supporting the rise-time, intensity, and duration of emotional experiences. Critically, the different neural, peripheral, subjective, and behavioral measures of emotional responding unfold along unique timescales. For example, emotional responses captured by EEG occur more quickly than responses captured by skin conductance. Further, not only do the different indicators of emotional responses occur on different timescales, but their respective time courses can be relatively independent from each other. For example, the chronometry of biological measures may not always reflect the time course of subjective emotional experience or behavior (Mauss et al., 2005). Resolving the disparate time scales of emotional responding and connecting neural, physiological, behavioral, and subjective emotion signals remain a central challenge of emotion research (Davidson, 2015) and remains critical to determine how neural firing, unfolding over milliseconds is linked to subjective feeling states which, from one's introspection, last substantially longer.

References

Alexander, G. E., DeLong, M. R., & Strick, P. L. (1986). Parallel organization of functionally segregated circuits linking basal ganglia and cortex. *Annual Review of Neuroscience, 9*(1), 357–381.

Amting, J. M., Greening, S. G., & Mitchell, D. G. V. (2010). Multiple mechanisms of consciousness: The neural correlates of emotional awareness. *Journal of Neuroscience, 30*(30), 10039–10047. https://doi.org/10.1523/JNEUROSCI.6434-09.2010

Andalman, A. S., Burns, V. M., Lovett-Barron, M., Broxton, M., Poole, B., Yang, S. J., Grosenick, L., Lerner, T. N., Chen, R., Benster, T., Mourrain, P., Levoy, M., Rajan, K., & Deisseroth, K. (2019). Neuronal dynamics regulating brain and behavioral state transitions. *Cell, 177*(4), 970–985.e20. https://doi.org/10.1016/j.cell.2019.02.037

Anderson, D. J., & Adolphs, R. (2014). A framework for studying emotions across species. *Cell, 157*(1), 187–200. https://doi.org/10.1016/j.cell.2014.03.003

Aoki, S., Smith, J. B., Li, H., Yan, X., Igarashi, M., Coulon, P., Wickens, J. R., Ruigrok, T. J., & Jin, X. (2019). An open cortico-basal ganglia loop allows limbic control over motor output via the nigrothalamic pathway. *eLife, 8*, e49995. https://doi.org/10.7554/eLife.49995

Asok, A., Kandel, E. R., & Rayman, J. B. (2019). The neurobiology of fear generalization. *Frontiers in Behavioral Neuroscience, 12*, 329.

Awh, E., & Vogel, E. K. (2008). The bouncer in the brain. *Nature Neuroscience, 11*(1), 5–6. https://doi.org/10.1038/nn0108-5

Barlow, R. L., Gorges, M., Wearn, A., Niessen, H. G., Kassubek, J., Dalley, J. W., & Pekcec, A. (2018). Ventral striatal D2/3 receptor availability is associated with impulsive choice behavior as well as limbic corticostriatal connectivity. *International Journal of Neuropsychopharmacology, 21*(7), 705–715. https://doi.org/10.1093/ijnp/pyy030

Berridge, K. C. (2019). Affective valence in the brain: Modules or modes? *Nature Reviews Neuroscience, 20*(4), 225–234. https://doi.org/10.1038/s41583-019-0122-8

Berridge, K. C., & Kringelbach, M. L. (2015). Pleasure systems in the brain. *Neuron, 86*(3), 646–664. https://doi.org/10.1016/j.neuron.2015.02.018

Beyeler, A., Chang, C.-J., Silvestre, M., Lévêque, C., Namburi, P., Wildes, C. P., & Tye, K. M. (2018). Organization of valence-encoding and projection-defined neurons in the basolateral amygdala. *Cell Reports, 22*(4), 905–918.

Blanchard, R. J., Blanchard, D. C., Rodgers, J., & Weiss, S. M. (1990). The characterization and modelling of antipredator defensive behavior. *Neuroscience & Biobehavioral Reviews, 14*(4), 463–472. https://doi.org/10.1016/S0149-7634(05)80069-7

Bliss-Moreau, E., & Rudebeck, P. H. (2021). Animal models of human mood. *Neuroscience & Biobehavioral Reviews, 120*, 574–582. https://doi.org/10.1016/j.neubiorev.2020.06.024

Bocchio, M., Nabavi, S., & Capogna, M. (2017). Synaptic plasticity, engrams, and network oscillations in amygdala circuits for storage and retrieval of emotional memories. *Neuron, 94*(4), 731–743. https://doi.org/10.1016/j.neuron.2017.03.022

Borji, A., & Itti, L. (2010). *State-of-the-art in visual attention modeling*.

Bradley, M. M., & Lang, P. J. (2000). Measuring emotion: Behavior, feeling, and physiology. In *Cognitive neuroscience of emotion* (pp. 242–276). Oxford University Press.

Bublatzky, F., Kavcıoğlu, F., Guerra, P., Doll, S., & Junghöfer, M. (2020). Contextual information resolves uncertainty about ambiguous facial emotions: Behavioral and magnetoencephalographic correlates. *NeuroImage, 215*, 116814. https://doi.org/10.1016/j.neuroimage.2020.116814

Buckholtz, J. W., Treadway, M. T., Cowan, R. L., Woodward, N. D., Li, R., Ansari, M. S., Baldwin, R. M., Schwartzman, A. N., Shelby, E. S., Smith, C. E., Kessler, R. M., & Zald, D. H. (2010). Dopaminergic network differences in human impulsivity. *Science (New York, N.Y.), 329*(5991), 532. https://doi.org/10.1126/science.1185778

Buzsáki, G., Anastassiou, C. A., & Koch, C. (2012). The origin of extracellular fields and currents—EEG, ECoG, LFP and spikes. *Nature Reviews Neuroscience, 13*(6), 407–420. https://doi.org/10.1038/nrn3241

Cacioppo, J. T., Petty, R. E., Losch, M. E., & Kim, H. S. (1986). Electromyographic activity over facial muscle regions can differentiate the valence and intensity of affective reactions. *Journal of Personality and Social Psychology, 50*(2), 260.

Calhoon, G. G., & Tye, K. M. (2015). Resolving the neural circuits of anxiety. *Nature Neuroscience, 18*(10), 1394–1404. https://doi.org/10.1038/nn.4101

Castro, D. C., & Berridge, K. C. (2014). Opioid hedonic hotspot in nucleus accumbens shell: Mu, delta, and kappa maps for enhancement of sweetness “liking” and “wanting”. *Journal of Neuroscience, 34*(12), 4239–4250. https://doi.org/10.1523/JNEUROSCI.4458-13.2014

Castro, D. C., & Berridge, K. C. (2017). Opioid and orexin hedonic hotspots in rat orbitofrontal cortex and insula. *Proceedings of the National Academy of Sciences, 114*(43), E9125–E9134. https://doi.org/10.1073/pnas.1705753114

Cermak, N., Stephanie, K. Y., Clark, R., Huang, Y.-C., Baskoylu, S. N., & Flavell, S. W. (2020). Whole-organism behavioral profiling reveals a role for dopamine in state-dependent motor program coupling in *C. elegans*. *eLife, 9*, e57093.

Chang, L. J., Gianaros, P. J., Manuck, S. B., Krishnan, A., & Wager, T. D. (2015). A sensitive and specific neural signature for picture-induced negative affect. *PLoS Biology, 13*(6), e1002180. https://doi.org/10.1371/journal.pbio.1002180

Chatham, C. H., & Badre, D. (2015). Multiple gates on working memory. *Current Opinion in Behavioral Sciences, 1*, 23–31. https://doi.org/10.1016/j.cobeha.2014.08.001

Ciocchi, S., Herry, C., Grenier, F., Wolff, S. B., Letzkus, J. J., Vlachos, I., Ehrlich, I., Sprengel, R., Deisseroth, K., & Stadler, M. B. (2010). Encoding of conditioned fear in central amygdala inhibitory circuits. *Nature, 468*(7321), 277–282.

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences, 36*(3), 181–204. https://doi.org/10.1017/S0140525X12000477

Csicsvari, J., Henze, D. A., Jamieson, B., Harris, K. D., Sirota, A., Barthó, P., Wise, K. D., & Buzsáki, G. (2003). Massively parallel recording of unit and local field potentials with silicon-based electrodes. *Journal of Neurophysiology, 90*(2), 1314–1323. https://doi.org/10.1152/jn.00116.2003

Dalley, J. W., & Robbins, T. W. (2017). Fractionating impulsivity: Neuropsychiatric implications. Nature Reviews. *Neuroscience, 18*(3), 158–171. https://doi.org/10.1038/nrn.2017.8

Darvas, F., Pantazis, D., Kucukaltun-Yildirim, E., & Leahy, R. M. (2004). Mapping human brain function with MEG and EEG: Methods and validation. *NeuroImage, 23*, S289–S299. https://doi.org/10.1016/j.neuroimage.2004.07.014

Davidson, R. J. (1998). Affective style and affective disorders: Perspectives from affective neuroscience. *Cognition & Emotion, 12*(3), 307–330.

Davidson, R. J. (2002). Anxiety and affective style: Role of prefrontal cortex and amygdala. *Biological Psychiatry, 51*(1), 68–80. https://doi.org/10.1016/S0006-3223(01)01328-2

Davidson, R. J. (2015). Comment: Affective chronometry has come of age. *Emotion Review, 7*(4), 368–370. https://doi.org/10.1177/1754073915590844

Davis, M., Walker, D. L., Miles, L., & Grillon, C. (2010). Phasic vs sustained fear in rats and humans: Role of the extended amygdala in fear vs anxiety. *Neuropsychopharmacology, 35*(1), 105–135. https://doi.org/10.1038/npp.2009.109

Davis, R. C. (1934). Modification of the galvanic reflex by daily repetition of a stimulus. *Journal of Experimental Psychology, 17*(4), 504.

Daw, N. D., Niv, Y., & Dayan, P. (2006). Actions, policies, values, and the basal ganglia. *Recent Breakthroughs in Basal Ganglia Research, 10*(9), 1214–1221.

Dzafic, I., Oestreich, L., Martin, A. K., Mowry, B., & Burianová, H. (2019). Stria terminalis, amygdala, and temporoparietal junction networks facilitate efficient emotion processing under expectations. *Human Brain Mapping, 40*(18), 5382–5396. https://doi.org/10.1002/hbm.24779

Fadok, J. P., Markovic, M., Tovote, P., & Lüthi, A. (2018). New perspectives on central amygdala function. *Current Opinion in Neurobiology, 49*, 141–147. https://doi.org/10.1016/j.conb.2018.02.009

Fanselow, M. S., & Lester, L. S. (1988). A functional behavioristic approach to aversively motivated behavior: Predatory imminence as a determinant of the topography of defensive behavior. In *Evolution and learning* (pp. 185–212). Lawrence Erlbaum Associates.

Fecteau, J. H., & Munoz, D. P. (2006). Salience, relevance, and firing: A priority map for target selection. *Trends in Cognitive Sciences, 10*(8), 382–390. https://doi.org/10.1016/j.tics.2006.06.011

Fellous, J.-M. (1999). Neuromodulatory basis of emotion. *The Neuroscientist, 5*(5), 283–294. https://doi.org/10.1177/107385849900500514

Fenno, L., Yizhar, O., & Deisseroth, K. (2011). The development and application of optogenetics. *Annual Review of Neuroscience, 34*(1), 389–412. https://doi.org/10.1146/annurev-neuro-061010-113817

Flavell, S. W., Pokala, N., Macosko, E. Z., Albrecht, D. R., Larsch, J., & Bargmann, C. I. (2013). Serotonin and the neuropeptide PDF initiate and extend opposing behavioral states in *C. elegans*. *Cell, 154*(5), 1023–1035. https://doi.org/10.1016/j.cell.2013.08.001

Fox, A. S., & Shackman, A. J. (2019). The central extended amygdala in fear and anxiety: Closing the gap between mechanistic and neuroimaging research. *Neuroscience Letters, 693*, 58–67. https://doi.org/10.1016/j.neulet.2017.11.056

Frijda, N. H., Mesquita, B., Sonnemans, J., & Van Goozen, S. (1991). *The duration of affective phenomena or emotions, sentiments and passions* (pp. 187–225). Wiley. https://lirias.kuleuven.be/retrieve/311014

Frijda, N. H. (1988). The laws of emotion. *American Psychologist, 43*(5), 349–358. https://doi.org/10.1037/0003-066X.43.5.349

Friston, K. J., Daunizeau, J., & Kiebel, S. J. (2009). Reinforcement learning or active inference? *PLoS One, 4*(7), e6421. https://doi.org/10.1371/journal.pone.0006421

Garrido, M. I., Barnes, G. R., Sahani, M., & Dolan, R. J. (2012). Functional evidence for a dual route to amygdala. *Current Biology, 22*(2), 129–134. https://doi.org/10.1016/j.cub.2011.11.056

Gibson, W. T., Gonzalez, C. R., Fernandez, C., Ramasamy, L., Tabachnik, T., Du, R. R., Felsen, P. D., Maire, M. R., Perona, P., & Anderson, D. J. (2015). Behavioral responses to a repetitive visual threat stimulus express a persistent state of defensive arousal in Drosophila. *Current Biology: CB, 25*(11), 1401–1415. https://doi.org/10.1016/j.cub.2015.03.058

Grace, A. A., & Rosenkranz, J. A. (2002). Regulation of conditioned responses of basolateral amygdala neurons. *Physiology & Behavior, 77*(4–5), 489–493.

Graybiel, A. M. (1998). The basal ganglia and chunking of action repertoires. *Neurobiology of Learning and Memory, 70*(1–2), 119–136. https://doi.org/10.1006/nlme.1998.3843

Gruber, A. J., Dayan, P., Gutkin, B. S., & Solla, S. A. (2006). Dopamine modulation in the basal ganglia locks the gate to working memory. *Journal of Computational Neuroscience, 20*(2), 153. https://doi.org/10.1007/s10827-005-5705-x

Gründemann, J., Bitterman, Y., Lu, T., Krabbe, S., Grewe, B. F., Schnitzer, M. J., & Lüthi, A. (2019). Amygdala ensembles encode behavioral states. *Science (New York, N.Y.), 364*(6437). https://doi.org/10.1126/science.aav8736

Gurney, K. N., Humphries, M. D., & Redgrave, P. (2015). A new framework for cortico-striatal plasticity: Behavioural theory meets in vitro data at the reinforcement-action interface. *PLoS Biology, 13*(1), e1002034. https://doi.org/10.1371/journal.pbio.1002034

Guru, A., Post, R. J., Ho, Y.-Y., & Warden, M. R. (2015). Making sense of optogenetics. *International Journal of Neuropsychopharmacology, 18*(11). https://doi.org/10.1093/ijnp/pyv079

Hansen, P., Kringelbach, M., & Salmelin, R. (2010). *MEG: An Introduction to Methods*. Oxford University Press.

Heller, A. (2018). Emotions aren't maladaptive. In *The nature of emotion: Fundamental questions* (2nd ed.). Oxford University Press.

Heller, A. S., Lapate, R. C., Mayer, K. E., & Davidson, R. J. (2014). The face of negative affect: Trial-by-trial corrugator responses to negative pictures are positively associated with amygdala and negatively associated with ventromedial prefrontal cortex activity. *Journal of Cognitive Neuroscience, 26*(9), 2102–2110. https://doi.org/10.1162/jocn_a_00622

Henze, D. A., Borhegyi, Z., Csicsvari, J., Mamiya, A., Harris, K. D., & Buzsáki, G. (2000). Intracellular features predicted by extracellular recordings in the hippocampus in vivo. *Journal of Neurophysiology, 84*(1), 390–400. https://doi.org/10.1152/jn.2000.84.1.390

Homma, I., & Masaoka, Y. (2008). Breathing rhythms and emotions. *Experimental Physiology, 93*(9), 1011–1021.

Hubbard, N. A., Romeo, R. R., Grotzinger, H., Giebler, M., Imhof, A., Bauer, C. C. C., & Gabrieli, J. D. E. (2020). Reward-sensitive basal ganglia stabilize the maintenance of goal-relevant neural patterns in adolescents. *Journal of Cognitive Neuroscience, 32*(8), 1508–1524. https://doi.org/10.1162/jocn_a_01572

Inagaki, H. K., Fontolan, L., Romani, S., & Svoboda, K. (2019). Discrete attractor dynamics underlies persistent activity in the frontal cortex. *Nature, 566*(7743), 212–217. https://doi.org/10.1038/s41586-019-0919-7

Inman, C. S., Bijanki, K. R., Bass, D. I., Gross, R. E., Hamann, S., & Willie, J. T. (2020). Human amygdala stimulation effects on emotion physiology and emotional experience. *Neuropsychologia, 145*, 106722. https://doi.org/10.1016/j.neuropsychologia.2018.03.019

Itti, L., Koch, C., & Niebur, E. (1998). A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 20*(11), 1254–1259. https://doi.org/10.1109/34.730558

Jacob, S. N., Stalter, M., & Nieder, A. (2016). Cell-type-specific modulation of targets and distractors by dopamine D1 receptors in primate prefrontal cortex. *Nature Communications, 7*(1), 13218. https://doi.org/10.1038/ncomms13218

Ji, N., Madan, G. K., Fabre, G. I., Dayan, A., Baker, C. M., Nwabudike, I., & Flavell, S. W. (2020). A neural circuit for flexible control of persistent behavioral states. *BioRxiv, 2020*(02), 04.934547. https://doi.org/10.1101/2020.02.04.934547

Johansen, J. P., Hamanaka, H., Monfils, M. H., Behnia, R., Deisseroth, K., Blair, H. T., & LeDoux, J. E. (2010). Optical activation of lateral amygdala pyramidal cells instructs associative fear learning. *Proceedings of the National Academy of Sciences, 107*(28), 12692–12697. https://doi.org/10.1073/pnas.1002418107

John, Y. J., Zikopoulos, B., Bullock, D., & Barbas, H. (2016). The emotional gatekeeper: A computational model of attentional selection and suppression through the pathway from the amygdala to the inhibitory thalamic reticular nucleus. *PLoS Computational Biology, 12*(2), e1004722. https://doi.org/10.1371/journal.pcbi.1004722

Jung, Y., Kennedy, A., Chiu, H., Mohammad, F., Claridge-Chang, A., & Anderson, D. J. (2020). Neurons that function within an integrator to promote a persistent behavioral state in drosophila. *Neuron, 105*(2), 322–333.e5. https://doi.org/10.1016/j.neuron.2019.10.028

Karalis, N., Dejean, C., Chaudun, F., Khoder, S., Rozeske, R. R., Wurtz, H., Bagur, S., Benchenane, K., Sirota, A., Courtin, J., & Herry, C. (2016). 4-Hz oscillations synchronize prefrontal–amygdala circuits during fear behavior. *Nature Neuroscience, 19*(4), 605–612. https://doi.org/10.1038/nn.4251

Kennedy, A., Kunwar, P. S., Li, L., Stagkourakis, S., Wagenaar, D. A., & Anderson, D. J. (2020). Stimulus-specific hypothalamic encoding of a persistent defensive state. *Nature, 586*(7831), 730–734. https://doi.org/10.1038/s41586-020-2728-4

Kirschstein, T., & Köhling, R. (2009). What is the Source of the EEG? *Clinical EEG and Neuroscience, 40*(3), 146–149. https://doi.org/10.1177/155005940904000305

Kringelbach, M. L., & Rolls, E. T. (2004). The functional neuroanatomy of the human orbitofrontal cortex: Evidence from neuroimaging and neuropsychology. *Progress in Neurobiology, 72*(5), 341–372. https://doi.org/10.1016/j.pneurobio.2004.03.006

Kim, S. Y., Adhikari, A., Lee, S. Y., Marshel, J. H., Kim, C. K., Mallory, C. S., Lo, M., Pak, S., Mattis, J., Lim, B. K., Malenka, R. C., Warden, M. R., Neve, R., Tye, K. M., & Deisseroth, K. (2013). Diverging neural pathways assemble a behavioural state from separable features in anxiety. *Nature, 496*(7444), 219–223. https://doi.org/10.1038/nature12018

Klumpers, F., Morgan, B., Terburg, D., Stein, D. J., & van Honk, J. (2015). Impaired acquisition of classically conditioned fear-potentiated startle reflexes in humans with focal bilateral basolateral amygdala damage. *Social Cognitive and Affective Neuroscience, 10*(9), 1161–1168. https://doi.org/10.1093/scan/nsu164

Knutson, B., & Cooper, J. C. (2005). Functional magnetic resonance imaging of reward prediction. *Current Opinion in Neurology, 18*(4), 411–417. https://doi.org/10.1097/01.wco.0000173463.24758.f6

Kringelbach, M. L., Stein, A., & van Hartevelt, T. J. (2012). The functional human neuroanatomy of food pleasure cycles. *Physiology & Behavior, 106*(3), 307–316. https://doi.org/10.1016/j.physbeh.2012.03.023

Lang, P. J., Greenwald, M. K., Bradley, M. M., & Hamm, A. O. (1993). Looking at pictures: Affective, facial, visceral, and behavioral reactions. *Psychophysiology, 30*(3), 261–273.

Lapate, R. C., Samaha, J., Rokers, B., Hamzah, H., Postle, B. R., & Davidson, R. J. (2017). Inhibition of Lateral Prefrontal Cortex Produces Emotionally Biased First Impressions: A Transcranial Magnetic Stimulation and Electroencephalography Study. *Psychological Science, 28*(7), 942–953. https://doi.org/10.1177/0956797617699837

LeDoux, J. E., Cicchetti, P., Xagoraris, A., & Romanski, L. M. (1990). The lateral amygdaloid nucleus: Sensory interface of the amygdala in fear conditioning. *Journal of Neuroscience, 10*(4), 1062–1069. https://doi.org/10.1523/JNEUROSCI.10-04-01062.1990

LeDoux, J. E. (2000). Emotion circuits in the brain. *Annual Review of Neuroscience, 23*(1), 155–184. https://doi.org/10.1146/annurev.neuro.23.1.155

LeDoux, J. E. (1996). The emotional brain: The mysterious underpinnings of emotional life. Simon & Schuster

Lee, S.-C., Amir, A., Haufler, D., & Pare, D. (2017). Differential recruitment of competing valence-related amygdala networks during anxiety. *Neuron, 96*(1), 81–88.e5. https://doi.org/10.1016/j.neuron.2017.09.002

Lee, S.-H., & Dan, Y. (2012). Neuromodulation of brain states. *Neuron, 76*(1), 209–222. https://doi.org/10.1016/j.neuron.2012.09.012

Lesting, J., Daldrup, T., Narayanan, V., Himpe, C., Seidenbecher, T., & Pape, H.-C. (2013). Directional theta coherence in prefrontal cortical to amygdalo-hippocampal pathways signals fear extinction. *PLoS One, 8*(10), e77707.

Leung, K., Mohammadi, A., Ryu, W. S., & Nemenman, I. (2016). Stereotypical escape behavior in caenorhabditis elegans allows quantification of effective heat stimulus level. *PLoS Computational Biology, 12*(12), e1005262. https://doi.org/10.1371/journal.pcbi.1005262

Li, Z. (2002). A saliency map in primary visual cortex. *Trends in Cognitive Sciences, 6*(1), 9–16.

Likhtik, E., & Johansen, J. P. (2019). Neuromodulation in circuits of aversive emotional learning. *Nature Neuroscience, 22*(10), 1586–1597. https://doi.org/10.1038/s41593-019-0503-3

MacNiven, K. H., Leong, J. K., & Knutson, B. (2020). Medial forebrain bundle structure is linked to human impulsivity. *Science Advances, 6*(38), eaba4788. https://doi.org/10.1126/sciadv.aba4788

Maffei, A., & Angrilli, A. (2019). Spontaneous blink rate as an index of attention and emotion during film clips viewing. *Physiology & Behavior, 204*, 256–263. https://doi.org/10.1016/j.physbeh.2019.02.037

Major, G., & Tank, D. (2004). Persistent neural activity: Prevalence and mechanisms. *Current Opinion in Neurobiology, 14*(6), 675–684. https://doi.org/10.1016/j.conb.2004.10.017

Marder, E. (2012). Neuromodulation of neuronal circuits: Back to the future. *Neuron, 76*(1), 1–11. https://doi.org/10.1016/j.neuron.2012.09.010

Mattavelli, G., Cattaneo, Z., & Papagno, C. (2011). Transcranial magnetic stimulation of medial prefrontal cortex modulates face expressions processing in a priming task. *Neuropsychologia, 49*(5), 992–998. https://doi.org/10.1016/j.neuropsychologia.2011.01.038

Mauss, I. B., Levenson, R. W., McCarter, L., Wilhelm, F. H., & Gross, J. J. (2005). The tie that binds? Coherence among emotion experience, behavior, and physiology. *Emotion, 5*(2), 175.

Mauss, I. B., & Robinson, M. D. (2009). Measures of emotion: A review. *Cognition & Emotion, 23*(2), 209–237. https://doi.org/10.1080/02699930802204677

McAlonan, K., Cavanaugh, J., & Wurtz, R. H. (2006). Attentional modulation of thalamic reticular neurons. *Journal of Neuroscience, 26*(16), 4444–4450.

McDonald, A. J. (1998). Cortical pathways to the mammalian amygdala. *Progress in Neurobiology, 55*(3), 257–332. https://doi.org/10.1016/S0301-0082(98)00003-3

McFadyen, J. (2019). Investigating the subcortical route to the amygdala across species and in disordered fear responses. *Journal of Experimental Neuroscience, 13*. https://doi.org/10.1177/1179069519846445

McFadyen, J., Mermillod, M., Mattingley, J. B., Halász, V., & Garrido, M. I. (2017). A rapid subcortical amygdala route for faces irrespective of spatial frequency and emotion. *The Journal of Neuroscience, 37*(14), 3864–3874. https://doi.org/10.1523/JNEUROSCI.3525-16.2017

McNab, F., & Klingberg, T. (2008). Prefrontal cortex and basal ganglia control access to working memory. *Nature Neuroscience, 11*(1), 103–107. https://doi.org/10.1038/nn2024

McNaughton, N., & Corr, P. J. (2018). Survival circuits and risk assessment. *Current Opinion in Behavioral Sciences, 24*, 14–20. https://doi.org/10.1016/j.cobeha.2018.01.018

Méndez-Bértolo, C., Moratti, S., Toledano, R., Lopez-Sosa, F., Martínez-Alvarez, R., Mah, Y. H., Vuilleumier, P., Gil-Nagel, A., & Strange, B. A. (2016). A fast pathway for fear in human amygdala. *Nature Neuroscience, 19*(8), 1041–1049. https://doi.org/10.1038/nn.4324

Mesulam, M. M. (1998). From sensation to cognition. *Brain: A Journal of Neurology, 121*(6), 1013–1052. https://doi.org/10.1093/brain/121.6.1013

Meyer, C., Padmala, S., & Pessoa, L. (2019). Dynamic threat processing. *Journal of Cognitive Neuroscience, 31*(4), 522–542. https://doi.org/10.1162/jocn_a_01363

Mitchell, D. G. V., & Greening, S. G. (2012). Conscious perception of emotional stimuli: Brain mechanisms. *The Neuroscientist, 18*(4), 386–398. https://doi.org/10.1177/1073858411416515

Mobbs, D., & Kim, J. J. (2015). Neuroethological studies of fear, anxiety, and risky decision-making in rodents and humans. *Current Opinion in Behavioral Sciences, 5*, 8–15. https://doi.org/10.1016/j.cobeha.2015.06.005

Mobbs, D., Petrovic, P., Marchant, J. L., Hassabis, D., Weiskopf, N., Seymour, B., Dolan, R. J., & Frith, C. D. (2007). When fear is near: Threat imminence elicits prefrontal-periaqueductal gray shifts in humans. *Science, 317*(5841), 1079–1083. https://doi.org/10.1126/science.1144298

Mobbs, D., Yu, R., Rowe, J. B., Eich, H., FeldmanHall, O., & Dalgleish, T. (2010). Neural activity associated with monitoring the oscillating threat value of a tarantula. *Proceedings of the National Academy of Sciences of the United States of America, 107*(47), 20582–20586. https://doi.org/10.1073/pnas.1009076107

Mobini, S., Body, S., Ho, M. Y., Bradshaw, C. M., Szabadi, E., Deakin, J. F. W., & Anderson, I. M. (2002). Effects of lesions of the orbitofrontal cortex on sensitivity to delayed and probabilistic reinforcement. *Psychopharmacology, 160*(3), 290–298. https://doi.org/10.1007/s00213-001-0983-0

Morris, J. S., Öhman, A., & Dolan, R. J. (1999). A subcortical pathway to the right amygdala mediating "unseen" fear. *Proceedings of the National Academy of Sciences, 96*(4), 1680–1685. https://doi.org/10.1073/pnas.96.4.1680

Namburi, P., Beyeler, A., Yorozu, S., Calhoon, G. G., Halbert, S. A., Wichmann, R., Holden, S. S., Mertens, K. L., Anahtar, M., Felix-Ortiz, A. C., Wickersham, I. R., Gray, J. M., & Tye, K. M. (2015). A circuit mechanism for differentiating positive and negative associations. *Nature, 520*(7549), 675–678. https://doi.org/10.1038/nature14366

Neta, M., & Tong, T. T. (2016). Don't like what you see? Give it time: Longer reaction times associated with increased positive affect. *Emotion, 16*(5), 730–739. https://doi.org/10.1037/emo0000181

Neta, M., Norris, C. J., & Whalen, P. J. (2009). Corrugator Muscle Responses Are Associated With Individual Differences in Positivity-Negativity Bias. *Emotion (Washington, D.C.), 9*(5), 640–648. https://doi.org/10.1037/a0016819

Öhman, A., Juth, P., & Lundqvist, D. (2010). Finding the face in a crowd: Relationships between distractor redundancy, target emotion, and target gender. *Cognition and Emotion, 24*(7), 1216–1228. https://doi.org/10.1080/02699930903166882

O'Reilly, R. C., & Frank, M. J. (2006). Making working memory work: A computational model of learning in the prefrontal cortex and basal ganglia. *Neural Computation, 18*(2), 283–328. https://doi.org/10.1162/089976606775093909

Panksepp, J. (2004). *Affective neuroscience: The foundations of human and animal emotions*. Oxford University Press.

Panksepp, J. (2011). The basic emotional circuits of mammalian brains: Do animals have affective lives? *Neuroscience and Biobehavioral Reviews, 35*(9), 1791–1804. https://doi.org/10.1016/j.neubiorev.2011.08.003

Pape, H. C., Narayanan, R. T., Smid, J., Stork, O., & Seidenbecher, T. (2005). Theta activity in neurons and networks of the amygdala related to long-term fear memory. *Hippocampus, 15*(7), 874–880.

Paton, J. J., Belova, M. A., Morrison, S. E., & Salzman, C. D. (2006). The primate amygdala represents the positive and negative value of visual stimuli during learning. *Nature, 439*(7078), 865–870.

Paz, R., Bauer, E. P., & Paré, D. (2008). Theta synchronizes the activity of medial prefrontal neurons during learning. *Learning & Memory, 15*(7), 524–531.

Pinault, D. (2004). The thalamic reticular nucleus: Structure, function and concept. *Brain Research Reviews, 46*(1), 1–31.

Poldrack, R. A., Nichols, T., & Mumford, J. (2011). Handbook of functional MRI data analysis. *Cambridge University Press.* https://doi.org/10.1017/CBO9780511895029

Pool, A.-H., & Scott, K. (2014). Feeding regulation in Drosophila. *Current Opinion in Neurobiology, 29*, 57–63. https://doi.org/10.1016/j.conb.2014.05.008

Pourtois, G., Schettino, A., & Vuilleumier, P. (2013). Brain mechanisms for emotional influences on perception and attention: What is magic and what is not. *Biological Psychology, 92*(3), 492–512. https://doi.org/10.1016/j.biopsycho.2012.02.007

Powell, D. A., & Ginsberg, J. P. (2005). Single unit activity in the medial prefrontal cortex during pavlovian heart rate conditioning: Effects of peripheral autonomic blockade. *Neurobiology of Learning and Memory, 84*(3), 200–213. https://doi.org/10.1016/j.nlm.2005.08.001

Prosser, C. L., & Hunter, W. S. (1936). The extinction of startle responses and spinal reflexes in the white rat. *American Journal of Physiology-Legacy Content, 117*(4), 609–618. https://doi.org/10.1152/ajplegacy.1936.117.4.609

Quirk, G. J., Repa, C., & LeDoux, J. E. (1995). Fear conditioning enhances short-latency auditory responses of lateral amygdala neurons: Parallel recordings in the freely behaving rat. *Neuron, 15*(5), 1029–1039. https://doi.org/10.1016/0896-6273(95)90092-6

Randlett, O., Haesemeyer, M., Forkin, G., Shoenhard, H., Schier, A. F., Engert, F., & Granato, M. (2019). Distributed plasticity drives visual habituation learning in Larval Zebrafish. *Current Biology: CB, 29*(8), 1337–1345.e4. https://doi.org/10.1016/j.cub.2019.02.039

Redgrave, P., Vautrelle, N., & Reynolds, J. N. J. (2011). Functional properties of the basal ganglia's re-entrant loop architecture: Selection and reinforcement. *Neuroscience, 198*, 138–151. https://doi.org/10.1016/j.neuroscience.2011.07.060

Redish, A. D. (2016). Vicarious trial and error. *Nature Reviews Neuroscience, 17*(3), 147. https://doi.org/10.1038/nrn.2015.30

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology, 39*(6), 1161–1178. https://doi.org/10.1037/h0077714

Sah, P., Faber, E. L., Lopez de Armentia, M., & Power, J. (2003). The amygdaloid complex: Anatomy and physiology. *Physiological Reviews, 83*(3), 803–834.

Scherer, K. R. (2005). What are emotions? And how can they be measured? *Social Science Information, 44*(4), 695–729. https://doi.org/10.1177/0539018405058216

Seidenbecher, T., Laxmi, T. R., Stork, O., & Pape, H.-C. (2003). Amygdalar and hippocampal theta rhythm synchronization during fear memory retrieval. *Science, 301*(5634), 846–850.

Shabel, S. J., Proulx, C. D., Trias, A., Murphy, R. T., & Malinow, R. (2012). Input to the lateral habenula from the basal ganglia is excitatory, aversive, and suppressed by serotonin. *Neuron, 74*(3), 475–481. https://doi.org/10.1016/j.neuron.2012.02.037

Sharpe, M. J., Stalnaker, T., Schuck, N. W., Killcross, S., Schoenbaum, G., & Niv, Y. (2019). An integrated model of action selection: Distinct modes of cortical control of striatal decision making. *Annual Review of Psychology, 70*(1), 53–76. https://doi.org/10.1146/annurev-psych-010418-102824

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology, 4*(1), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Small, D. M., Zatorre, R. J., Dagher, A., Evans, A. C., & Jones-Gotman, M. (2001). Changes in brain activity related to eating chocolate: From pleasure to aversion. *Brain: A Journal of Neurology, 124*(Pt 9), 1720–1733. https://doi.org/10.1093/brain/124.9.1720

Smith, K. S., Berridge, K. C., & Aldridge, J. W. (2011). Disentangling pleasure from incentive salience and learning signals in brain reward circuitry. *Proceedings of the National Academy of Sciences, 108*(27), E255–E264. https://doi.org/10.1073/pnas.1101920108

Sokolov, E. N. (1963). Higher nervous functions: The orienting reflex. *Annual Review of Physiology, 25*(1), 545–580. https://doi.org/10.1146/annurev.ph.25.030163.002553

Solomon, R. L., & Corbit, J. D. (1974). An opponent-process theory of motivation: I. Temporal dynamics of affect. *Psychological Review, 81*(2), 119–145. https://doi.org/10.1037/h0036128

Spruijt, B. M., Van Hooff, J. A., & Gispen, W. H. (1992). Ethology and neurobiology of grooming behavior. *Physiological Reviews, 72*(3), 825–852.

Stuber, G. D., Sparta, D. R., Stamatakis, A. M., van Leeuwen, W. A., Hardjoprajitno, J. E., Cho, S., Tye, K. M., Kempadoo, K. A., Zhang, F., Deisseroth, K., & Bonci, A. (2011). Excitatory transmission from the amygdala to nucleus accumbens facilitates reward seeking. *Nature, 475*(7356), 377–380. https://doi.org/10.1038/nature10194

Stujenske, J. M., O'Neill, P. K., Nahmoud, I., Goldberg, S., Diaz, L., Labkovich, M., Hardin, W., Bolkan, S. S., Reardon, T. R., Spellman, T. J., Salzman, C. D., Gordon, J. A., & Likhtik, E. (2020). Prelimbic-dependent activation of amygdala somatostatin interneurons signals non-aversive cues to promote discrimination [Preprint]. *Neuroscience*. https://doi.org/10.1101/2020.06.23.156018

Tanner, J., & Itti, L. (2019). A top-down saliency model with goal relevance. *Journal of Vision, 19*(1), 11–11. https://doi.org/10.1167/19.1.11

Thompson, R. F. (2009). Habituation: A history. *Neurobiology of Learning and Memory, 92*(2), 127–134. https://doi.org/10.1016/j.nlm.2008.07.011

Tomkins, S. S. (1978). Script theory: Differential magnification of affects. *Nebraska Symposium on Motivation, 26*, 201–236.

Tye, K. M., Stuber, G. D., de Ridder, B., Bonci, A., & Janak, P. H. (2008). Rapid strengthening of thalamo-amygdala synapses mediates cue–reward learning. *Nature, 453*(7199), 1253–1257. https://doi.org/10.1038/nature06963

Vander Weele, C. M., Siciliano, C. A., Matthews, G. A., Namburi, P., Izadmehr, E. M., Espinel, I. C., Nieh, E. H., Schut, E. H. S., Padilla-Coreano, N., Burgos-Robles, A., Chang, C.-J., Kimchi, E. Y., Beyeler, A., Wichmann, R., Wildes, C. P., & Tye, K. M. (2018). Dopamine enhances signal-to-noise ratio in cortical-brainstem encoding of aversive stimuli. *Nature, 563*(7731), 397–401. https://doi.org/10.1038/s41586-018-0682-1

Verduyn, P., Van Mechelen, I., Tuerlinckx, F., Meers, K., & Van Coillie, H. (2009). Intensity profiles of emotional experience over time. *Cognition and Emotion, 23*(7), 1427–1443. https://doi.org/10.1080/02699930902949031

Wager, T. D., Davidson, M. L., Hughes, B. L., Lindquist, M. A., & Ochsner, K. N. (2008). Prefrontal-subcortical pathways mediating successful emotion regulation. *Neuron, 59*(6), 1037–1050. https://doi.org/10.1016/j.neuron.2008.09.006

Waugh, C. E., Hamilton, J. P., & Gotlib, I. H. (2010). The neural temporal dynamics of the intensity of emotional experience. *NeuroImage, 49*(2), 1699–1707. https://doi.org/10.1016/j.neuroimage.2009.10.006

Waugh, C. E., Shing, E. Z., & Avery, B. M. (2015). Temporal dynamics of emotional processing in the brain. *Emotion Review, 7*(4), 323–329. https://doi.org/10.1177/1754073915590615

Waugh, C. E., Zarolia, P., Mauss, I. B., Lumian, D. S., Ford, B. Q., Davis, T. S., Ciesielski, B. G., Sams, K. V., & McRae, K. (2016). Emotion regulation changes the duration of the BOLD response to emotional stimuli. *Social Cognitive and Affective Neuroscience, 11*(10), 1550–1559. https://doi.org/10.1093/scan/nsw067

Welker, W. (1961). An analysis of exploratory and play behavior in animals. In *Functions of varied experience*. The Dorsey Press.

White, B. J., Berg, D. J., Kan, J. Y., Marino, R. A., Itti, L., & Munoz, D. P. (2017). Superior colliculus neurons encode a visual saliency map during free viewing of natural dynamic video. *Nature Communications, 8*(1), 14263. https://doi.org/10.1038/ncomms14263

Wilson, R. C., Takahashi, Y. K., Schoenbaum, G., & Niv, Y. (2014). Orbitofrontal cortex as a cognitive map of task space. *Neuron, 81*(2), 267–279. https://doi.org/10.1016/j.neuron.2013.11.005

Part II
Between-Episode Dynamics

Chapter 4
Emotional Inertia: On the Conservation of Emotional Momentum

Peter Koval, Patrick T. Burnett, and Yixia Zheng

Abstract Emotional inertia refers to the tendency for emotions/affective states to be resistant to change over time. In this chapter, we review a burgeoning literature documenting how emotional inertia differs between individuals and correlates with individual differences in personality, well-being and psychopathology; how inertia is (causally) related to other psychological and biological processes; and how emotional inertia can itself change over time within individuals. We begin with a brief overview of the historical origins of emotional inertia, before outlining how inertia is operationalized statistically, and how it relates to other indices of affect dynamics. Next, we provide a selective review of empirical research on emotional inertia, focusing especially on studies published in the past several years. In light of the empirical evidence, we discuss the plausibility of several distal and proximal explanatory mechanisms underlying emotional inertia at biological/neural and psychological levels. Finally, we conclude with a discussion of open questions and future directions for research on emotional inertia.

Keywords Emotional inertia · Affective inertia · (In)flexibility · Persistence · Resistance to change · Autocorrelation · Autoregressive · AR(1)

4.1 Introduction

What will the weather be like tomorrow? Your best guess, in the absence of other information, is to look at today's weather (Krzysztofowicz & Evans, 2008). This tendency for the past to predict the future, known as *temporal autocorrelation*, is a feature of many natural phenomena (Gottman, 1981), including human affect,

P. Koval (✉) · P. T. Burnett · Y. Zheng
Melbourne School of Psychological Sciences, The University of Melbourne,
Parkville, VIC, Australia
e-mail: p.koval@unimelb.edu.au; pburnett1@student.unimelb.edu.au;
yixia.zheng@student.unimelb.edu.au

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_4

where it is often labelled emotional or affective[1] "inertia". Put otherwise, *emotional* inertia refers to the tendency for the subjective, behavioural and/or physiological components of affective processes to be resistant to change, self-predictable, or persistent across time.

In this chapter, we review a burgeoning literature documenting how emotional inertia differs between individuals and correlates with individual differences in personality, well-being and psychopathology; how inertia is (causally) related to other psychological and biological processes; and how emotional inertia can itself change over time within individuals. We begin with a brief overview of historical origins before outlining how emotional inertia is statistically operationalized and how it relates to other indices of affect dynamics. Next, we provide a selective review of empirical research on emotional inertia, focusing on studies published in the past several years. In light of the empirical evidence, we discuss the plausibility of several distal and proximal explanatory mechanisms underlying emotional inertia at biological/neural and psychological levels. Finally, we conclude with a discussion of open questions and future directions for research on emotional inertia.

4.1.1 Historical Origins of Emotional Inertia

The term *emotional* inertia appears to have been first used by John Gottman and colleagues in their pioneering research on emotions in marital interactions (Cook et al., 1995). However, the application of time-series methods to study the dynamics of psychological processes (Gottman et al., 1969) and the use of autocorrelations to quantify mood dynamics (Huba et al., 1976) were proposed even earlier. In their application of these methods to the dynamics of marital interactions, Gottman and colleagues found that couples whose second-by-second emotional expressions were more autocorrelated, or "inert", tended to have lower relationship quality and a greater likelihood of divorce (Gottman et al., 2002). These authors argued that individuals with higher emotional inertia have a weaker homeostatic force that pulls emotions back towards baseline following perturbations, causing their emotions to persist over time (Cook et al., 1995). Thus, spouses with higher inertia are slower to recover from emotional upsets and "less open to being influenced by their partner" (Gottman et al., 2002 p. 332). However, Gottman and colleagues stopped short of proposing which factors might cause some individuals (or couples) to have higher emotional inertia than others.

Around the same time, Jerry Suls and colleagues proposed that the personality dimension of neuroticism may underlie individual differences in emotional inertia. In a series of diary and experience sampling studies, Suls and colleagues

---

[1] Although some scholars distinguish between "affect" and "emotion" (e.g., Gross, 2015), we use the terms interchangeably in line with common practice in studies on "emotional inertia" and the "affect/emotion dynamics" literature more broadly (e.g., Houben et al., 2015; Kuppens, 2015; Kuppens & Verduyn, 2017).

found that neuroticism was associated with heightened inertia of negative affect in daily life. Suls et al. described negative-affect inertia as a feature of the "neurotic cascade" (Suls et al., 1998; Suls & Martin, 2005), a constellation of mutually reinforcing mechanisms that underlie the daily emotional distress experienced by highly neurotic individuals. Among these, Suls and colleagues argued, is a greater tendency for negative feelings to "spillover" across contexts, driven in part by ineffective coping skills and an inability to adapt to recurrent stressors (Suls & Martin, 2005).

Gottman and Suls's work confirmed the "Law of Conservation of Emotional Momentum", proposed by Nico Frijda (1988, 2007), which holds that emotions are resistant to change over time unless acted upon by a force. Frijda was among the first to emphasize the inherently dynamical nature of emotions, which he argued change in proportion to fluctuating appraisals of internal/external events and (self-)regulatory forces. At the same time, however, Frijda argued that in the absence of such forces, emotions are inherently inert. Put otherwise, in opposition to the cliché that "time heals all wounds", Frijda (1988, 2007) argued that time, in itself, does not cause emotions to change. Rather, the default is emotional inertia or persistence.

4.2 Quantifying Emotional Inertia

The concept of emotional inertia is fundamentally about resistance to change over time. To study how emotions change or persist over time requires repeated measurement of emotions/affect sampled at a relatively high frequency, resulting in what is referred to as *intensive longitudinal data* (Bolger & Laurenceau, 2013; Walls & Schafer, 2006). In principle, emotional inertia could be quantified at any timescale, but it is typically operationalized as the (lag 1) autocorrelation of successive emotion measurements over seconds (e.g. Fairbairn & Sayette, 2013), minutes (e.g., Gilbert et al., 2019), hours (e.g., Nelson et al., 2020) or days (e.g., Brose et al., 2015).

Using intensive longitudinal emotion data, an individual's level of emotional inertia can be operationalized by estimating how their emotional intensity at occasion t, correlates with their emotion level at the previous occasion $t - 1$ (e.g. Huba et al., 1976; Koval et al., 2013b; Sperry et al., 2020). Autocorrelations can range from -1 to $+1$, with values closer to $+1$ indicating greater persistence in affect/emotion across successive measurement occasions and therefore higher emotional inertia.[2]

---

[2] Although relatively rare in the context of emotion, it is possible to obtain negative autocorrelations (cf. Rovine & Walls, 2006), which indicate an oscillatory process wherein high levels of the outcome are preceded by low levels and vice versa. This tends to produce positive autocorrelations at lag 2 (i.e., the correlation among scores at t and $t - 2$; Box et al., 2008).

A more common approach, however, is to model emotional inertia using a first-order autoregressive [AR(1)] model, in which a person's emotion at each occasion t is regressed onto their emotion at the previous occasion, $t - 1$, as shown in Eq. (4.1):

$$\text{emotion}_t = \alpha + \phi\left(\text{emotion}_{t-1}\right) + \epsilon_t \tag{4.1}$$

Here, the AR slope ϕ captures the degree to which emotions are self-predictable or persist across time (i.e., emotional inertia) and, like an autocorrelation, more positive AR slopes indicate greater occasion-to-occasion persistence, or inertia, of emotion.[3] Note that the AR(1) model contains two other parameters, which represent other important features of a person's affective trajectory over time.

The intercept α represents the current level of emotion when the previous level of emotion equals zero. When the lagged predictor emotion$_{t-1}$ is centered around its mean level—as is common practice (see Eq. 4.2, below)—the intercept α is equivalent to a person's mean level of emotion across all occasions (Hamaker & Grasman, 2015). This is convenient because the mean level of a stationary AR(1) process represents its "equilibrium" or "steady-state", which can be thought of as a person's emotional baseline, towards which their affective state tends to return following perturbations (de Haan-Rietdijk et al., 2016).

Finally, the residual term ϵ_t represents deviations in a person's current emotion (emotion$_t$) that are independent from their emotion at the previous occasion (emotion$_{t-1}$). These residuals are sometimes labeled "perturbations", "shocks" or "innovations" because they represent the influence of occasion-specific events that cause random changes in emotion (Hamaker, 2012; Jongerling et al., 2015). The variance of these residuals–denoted σ^2 and referred to as the *innovation variance*–captures the degree to which emotions vary as a function of all unobserved factors, including the types of emotional events people are exposed to and their reactivity to such events, as well as measurement error (Hamaker et al., 2018; Jongerling et al., 2015). Thus, collectively the three parameters of the AR(1) model represent three important features of affect dynamics: the emotional baseline (α), emotional inertia (ϕ), and residual emotional variation due to (random) events and other unobserved influences (σ^2).

4.2.1 The Multilevel AR(1) Model: Individual Differences in Emotional Inertia

In most research on emotional inertia, a multilevel extension of the AR(1) model described above has been applied, which allows researchers to simultaneously model data from multiple individuals (Rovine & Walls, 2006). In this approach, the intercept α_i and AR slope ϕ_i are allowed to vary randomly across individuals i (see

---

[3] AR slopes can fall outside the −1 to +1 range, indicating a non-stationary process wherein short-term fluctuations do not revert to a stable equilibrium but accumulate over time producing trends (Box et al., 2008). This highlights the need to detect and potentially control for trends when modeling inertia.

Eqs. 4.2–4.4)[4] and can be predicted by person-level characteristics (e.g., psychopathology, well-being, personality), represented by the generic person-level predictor Z_i in Eqs. (4.3)–(4.4), below:

$$\text{emotion}_{ti} = \alpha_i + \phi_i\left(\text{emotion}_{t-1i} - \overline{\text{emotion}_i}\right) + \epsilon_{ti} \tag{4.2}$$

$$\alpha_i = \beta_{00} + \beta_{01}\left(Z_i\right) + \mu_{0i} \tag{4.3}$$

$$\phi_i = \beta_{10} + \beta_{11}\left(Z_i\right) + \mu_{1i} \tag{4.4}$$

Note that the multilevel AR(1) model described above, which has been applied in the vast majority of studies on emotional inertia, assumes that the innovation variance σ^2 (i.e., the variance of the within-person residuals ϵ_{ti}) is the same for all individuals *i*. Put otherwise, individual differences in emotional variability due to exposure and/or reactivity to random and unobserved factors, such as emotional events, are not modelled. This has two consequences. First, it leads to bias in estimates of emotional inertia because all individual differences in how emotions vary over time must be captured by the AR slope ϕ_i, which is used to quantify inertia (Jongerling et al., 2015; Wang et al., 2012). Second, and more importantly, the standard multilevel AR(1) model likely represents an incomplete account of affect dynamics (cf. Kuppens et al., 2010b): although it can quantify how people differ in the extent to which their emotions carry over from moment-to-moment (i.e., inertia), it does not contain a parameter representing the degree to which people's emotions fluctuate in response to random occasion-specific influences, such as stressors, up-lifts etc.

4.2.1.1 Extensions to the Multilevel AR(1) Model

Several important developments in the statistical models used to quantify inertia have occurred in recent years. First, Jongerling et al. (2015) describe a multilevel AR(1) model that also allows for individual-specific innovation variances σ^2_i (see also Wang et al., 2012), which provides a more complete representation of how people's emotions vary over time, as a function of both predictable (inertia) and unpredictable (innovations) influences (see Fig. 4.1). Second, Hamaker et al. (2018) describe a multivariate extension of Jongerling et al.'s (2015) model, in which inertia and innovation variances of two or more dimensions of affect (e.g., positive and negative affect; valence and arousal) can be modelled simultaneously. This

---

[4] The within-person part of the multilevel AR(1) model is shown in Eq. (4.2) and the between-person part in Eqs. (4.3)–(4.4). The lagged predictor emotion_{t-1i} is centered around each person *i* 's mean emotion ($\overline{\text{emotion}_i}$). Although this is standard and ensures that all between-person variance is removed from the lagged predictor, this downwardly biases estimates of the AR slope (Hamaker & Grasman, 2015).

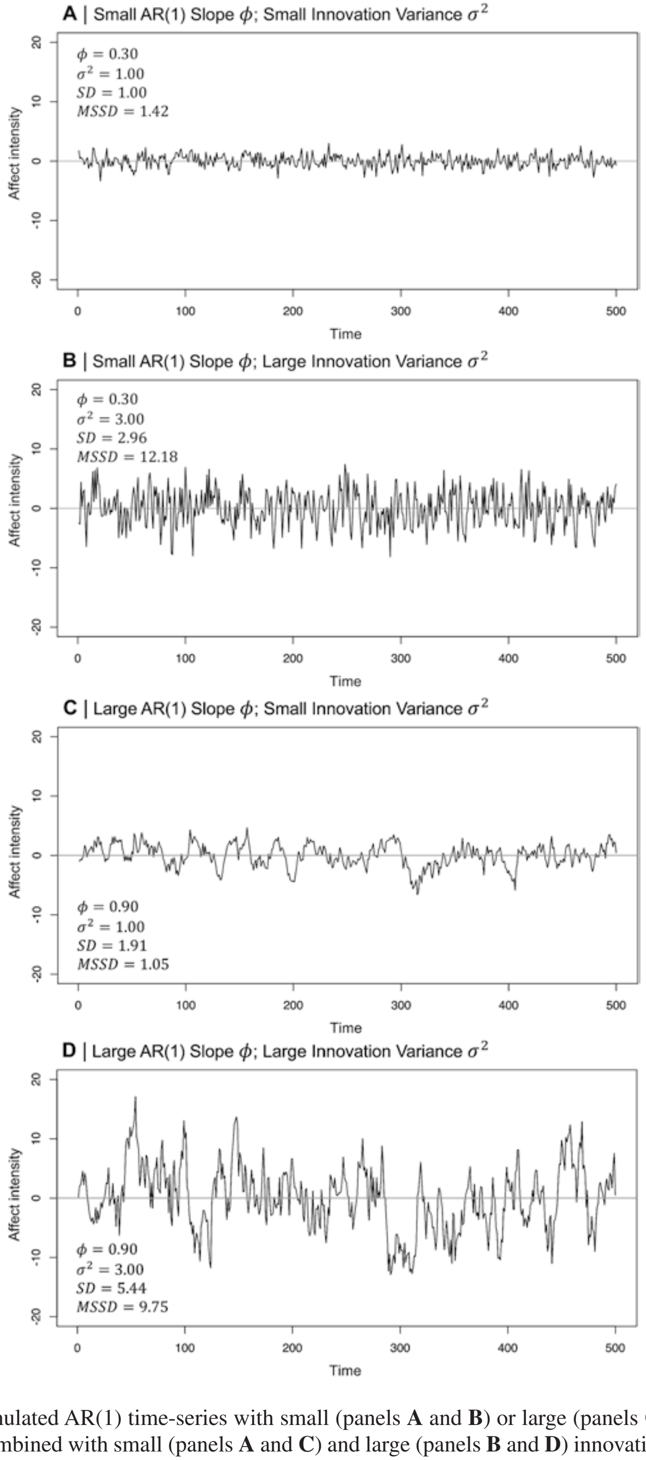


Fig. 4.1 Simulated AR(1) time-series with small (panels **A** and **B**) or large (panels **C** and **D**) AR slopes, ϕ, combined with small (panels **A** and **C**) and large (panels **B** and **D**) innovation variances, σ^2. All time-series have the same equilibrium or mean, μ. Varying the AR slope (ϕ) and innovation variance (σ^2) results in different levels of total variability (SD) and instability (MSSD)

multilevel vector autoregressive (VAR) model also includes cross-lagged effects representing how different dimensions of affect mutually influence each other over time, sometimes labelled augmentation and blunting effects (Kuppens & Verduyn, 2017; see also Krone et al., 2018). Third, Schuurman and Hamaker (2019) recently extended the multilevel VAR model to include measurement error, which allows researchers to differentiate systematic occasion-specific variability (i.e., innovation variance) from variance due to unsystematic measurement errors, which are otherwise confounded.

We discuss several other developments in the statistical modeling of emotional inertia later when reviewing research on within-person changes in inertia. However, one final issue to note is that the models discussed to this point are all discrete-time models, in which intervals between successive measurement occasions are assumed to be equal. This is often not the case in research on affect dynamics, in which emotions are commonly measured at random moments throughout the day using experience sampling methods. Several approaches have been proposed to deal with this (see De Haan-Rietdijk et al., 2017), including models that explicitly treat time as continuous (e.g., Kuppens et al., 2010b; Loossens et al., 2020) and models that use a discrete-time approximation to allow for unequally spaced measurement occasions (Hamaker et al., 2018).

4.2.1.2 Relations Between Emotional Inertia and Other Indices of Affect Dynamics

So far, we have discussed how emotional inertia is quantified. Yet, besides emotional inertia, researchers over the years have proposed a dizzying array of indices to characterize different dynamical properties of affect. For instance, Dejonckheere et al. (2019) identified 16 different indicators of affect dynamics (see also Houben et al., 2015). This diversity not only makes it difficult to navigate the literature, but also raises the question of how different measures of affect dynamics relate to each other. Two of the most common indices of affect dynamics, which have often been contrasted with inertia, are the standard deviation (*SD*) and the mean squared successive difference (*MSSD*; e.g., Gruber et al., 2013; Houben et al., 2015; Koval et al., 2013a, b). The *SD* captures the overall amplitude or range of a person's affective fluctuations around their mean and is therefore considered a measure of emotional "variability"–we refer to this as *net* variability to differentiate it from innovation variance discussed earlier.

Put otherwise, net variability (*SD*) reflects how much a person's emotions deviate from their affective baseline or equilibrium over a given period of time, regardless of the temporal order of emotional fluctuations. In contrast, the *MSSD* indexes the average magnitude of moment-to-moment affective fluctuations and is therefore considered a measure of emotional "instability". High levels of instability (*MSSD*) result from a combination of high net variability (*SD*) and low inertia (Jahng et al., 2008). Yet, the relations among inertia, net variability and instability are complex and somewhat counterintuitive (Houben et al., 2015).

To illustrate how these different indices of affect dynamics are related, Fig. 4.1 shows four simulated time-series based on an AR(1) model with small ($\phi = .3$) or large ($\phi = .9$) AR slopes, and small ($\sigma^2 = 1$) or large ($\sigma^2 = 3$) innovation variances. The hypothetical profiles of affect dynamics in Fig. 4.1 show that net variability (*SD*) is a function of the AR slope ϕ, representing inertia, and the innovation variance σ^2, representing exposure/reactivity to emotional events. Thus, for two people with the same innovation variance (e.g., compare Fig. 4.1 panels B vs. D, both of which have $\sigma^2 = 3$), a person with higher inertia will also have greater net variability (Fig. 4.1 panel D: $\phi = .9$ and $SD = 5.44$) than a person with lower inertia (Fig. 4.1 panel B: $\phi = .3$ and $SD = 2.96$). Similarly, given the same degree of emotional inertia (e.g., compare Fig. 4.1 panels A vs. B, both of which have $\phi = .3$), a person with a larger innovation variance will also be more emotionally variable (Fig. 4.1 panel B: $\sigma^2 = 3$ and $SD = 2.96$) than someone with a smaller innovation variance (Fig. 4.1 panel A: $\sigma^2 = 1$ and $SD = 1$). As illustrated in panel D of Fig. 4.1, this implies that high net emotional variability (*SD*) can co-exist with high inertia (AR slope), reflecting a tendency for large but slow changes in affect over time (e.g., Bos et al., 2018; Koval et al., 2013a, b; Nelson et al., 2020). Furthermore, panel D of Fig. 4.1 also illustrates that, although affective instability (*MSSD*) increases with higher net variability (*SD*) and lower inertia (AR slope), it is also possible for a person's affect to be both highly unstable and highly inert (see Koval et al., 2013a, b; Houben et al., 2015; Wang et al., 2012). This is because the MSSD is more strongly related to net variability than to inertia (see also, Dejonckheere et al., 2019).

These different measures of affect dynamics are often studied in isolation, leading to inconsistent conclusions about what constitutes "healthy" emotional functioning. Specifically, two main opposing theoretical perspectives exist within the literature, each supported by research using different indices of affect dynamics. On one hand, emotional stability is often considered essential for healthy functioning (e.g., Gruber et al., 2013), supported by evidence that higher net variability (*SD*) and instability (*MSSD*) are associated with worse well-being (Houben et al., 2015). On the other hand, the notion that psychological adjustment relies on emotional flexibility (Kashdan & Rottenberg, 2010) is also supported by robust evidence linking higher emotional inertia (AR slope) with poor well-being and psychopathology (Houben et al., 2015). These views can be reconciled by considering the relations among indices of affect dynamics, illustrated above. Specifically, healthy emotional functioning may involve affective changes that are neither highly variable, unstable, or inert. Put otherwise, in line with Suls and Martin's (2005) description of the "daily life of the garden variety neurotic", emotional maladjustment may involve a combination of heightened exposure/reactivity to stressful events (i.e., high innovation variance) and the tendency for emotions to be persistent across time (i.e., high AR slope or inertia). These two processes combine to produce a pattern of affect dynamics involving high inertia, yet also high net variability and instability (see Fig. 4.1, panel D).

4.3 Empirical Findings

Having reviewed how emotional inertia is quantified and how it relates to other indices of affect dynamics, we now turn our attention to the rapidly growing body of empirical research on emotional inertia. The publication that undoubtedly reignited this empirical literature was Kuppens et al. (2010a), which reported that individuals with low self-esteem and clinical depression showed heightened inertia of both their negative and positive emotions. Since Kuppens et al. (2010a) seminal paper, understanding how presumably stable individual differences in emotional inertia relate to depression has remained a major focus within the literature. However, emotional inertia has also been studied in relation to (symptoms of) other psychiatric disorders, as well as measures of well-being and personality. Finally, a smaller volume of research has investigated within-person changes in emotional inertia and explored potential causal mechanisms underlying inertia. In what follows, we provide a broad (yet not exhaustive) review of research on emotional inertia, focusing especially on research published since Houben et al.'s (2015) meta-analysis on the association between affect dynamics and psychological well-being.

In their synthesis of 120 effects from dozens of independent studies, Houben et al. (2015) found that emotional inertia is reliably negatively correlated with well-being ($r = -.15$). Although Houben et al. (2015) reported that associations between inertia and well-being differed substantially across studies, most of the potential moderators (e.g., age, timescale, use of clinical sample) they examined did not significantly explain this variability. One notable exception, however, was emotional valence. Specifically, Houben et al. (2015) reported that the inertia of negative affect (NA) was almost twice as strongly negatively correlated with well-being as the inertia of positive affect (PA). In light of Houben et al.'s (2015) findings, recent research has continued to focus predominantly on NA inertia.

4.3.1 Depression

Heightened inertia, especially of NA, assessed at a range of timescales has been linked with current and future symptoms and/or diagnosis of depression. Specifically, greater day-to-day inertia in NA has been associated with depression (Brose et al., 2015; Hamaker et al., 2018; Jenkins et al., 2020), as has NA inertia assessed at timescales of hours (Gilbert et al., 2019; Mneimne et al., 2018; Nelson et al., 2020; Wenze et al., 2009), minutes (Koval et al., 2013a, b, 2016) and seconds (Koval et al., 2012; Kuppens et al., 2010a, b, 2012). Moreover, in these studies emotions have been assessed using self-report methods (e.g., Jenkins et al., 2020; Koval et al., 2016) and observer coding of behavior (e.g., Kuppens et al., 2012; Koval et al., 2012). Thus, several studies measuring affect at different timescales and using various assessment methods have produced consistent evidence for an association between emotional inertia and depression (Houben et al., 2015). However, as we discuss below, less support for an association between depression and PA inertia exists and recent studies have even called into question the robustness of the relationship between NA inertia and depression.

4.3.1.1 Inertia of Non-Emotional Processes and Depression

Extending this line of research, two recent studies examined how depression relates to inertia of other cognitive/behavioral processes. Bean et al. (2020) examined the autoregressive slope of state rumination in daily life and found that individuals with higher depressive symptoms showed a higher degree of "ruminative inertia". Similarly, Emler et al. (2020) showed that severity of depressive symptoms was associated with an increased autoregressive slope of spending time alone, termed "solitude inertia". Furthermore, individuals with higher solitude inertia at baseline showed increases in depressive symptoms over 8 weeks (cf. Kuppens et al., 2012).

4.3.1.2 Inconsistent Findings Regarding the Depression-Inertia Association

A number of studies have yielded inconsistent findings in relation to the association between emotional inertia and depression. For example, Heller et al. (2018), Lamers et al. (2018), and Sperry et al. (2020) found no differences between clinically depressed and healthy individuals in terms of emotional inertia in daily life, replicating Thompson et al.'s (2012) findings. Likewise, Bosley et al. (2019) found no reliable association between emotional inertia and depressive symptom severity in a heterogenous clinical sample. In contrast to Kuppens et al., 2010a, b, 2012), Ogbaselase et al. (2020) reported no association between depressive symptoms and inertia of second-by-second emotional expressions in a sample of community adolescents. Finally, two recent studies showed that although depressive symptoms were associated with higher inertia, these associations were substantially diminished (in some cases no longer meaningfully different from zero) when controlling for overlap among inertia with mean and variability (*SD*) of affect (Bos et al., 2019; Houben & Kuppens, 2020). Similarly, in their analyses of 15 daily diary and ESM data sets, Dejonckheere et al. (2019) concluded that emotional inertia is not a unique predictor of depressive symptoms or diagnosis after controlling for mean levels and net variability in PA and NA.

4.3.1.3 Inertia of PA in Relation to Anhedonia

Although much of the research has focused on the association between NA inertia and depression, a few recent studies have investigated how anhedonia (a core symptom of depression involving alterations in PA functioning) is related to PA inertia.

Heininga et al. (2019) reported no differences in PA inertia between healthy controls and clinically depressed individuals with anhedonia. This replicated two previous studies reporting no observable differences in several parameters of PA dynamics, including inertia, among depressed individuals with anhedonia (Heininga et al., 2017; Van Roekel et al., 2016). Thus, even individuals who purportedly suffer from dysregulated positive emotionality do not necessarily show consistent differences in PA inertia. Finally, some evidence suggests that depression may actually be associated with *lower* PA inertia in daily life (Höhn et al., 2013; see also Jenkins et al., 2020, supplemental materials B).

4.3.1.4 Moderators of the Depression-Inertia Association

Taken together, the above studies suggest that emotional inertia may not be reliably associated with depression, either due to potentially unforeseen moderators or because inertia may not uniquely predict depression after accounting for its overlap with mean levels and net affective variability (Dejonckheere et al., 2019). Since the latter issue was discussed by Dejonckheere et al. (2019), we focus on the issue of potential moderators. We speculate that inconsistent findings across studies may be driven by differences in the degree to which depression is recurrent/persistent versus emerging. Specifically, emotional inertia may be more characteristic of increased *vulnerability* to future depressive episodes than a feature of affect dynamics among the *currently* depressed. This could explain why heightened inertia has been observed in (particularly young) people with elevated subclinical depressive symptoms (e.g., Koval et al., 2013a, b; Hamaker et al., 2018) and among adolescents with clinical depression (e.g., Kuppens et al., 2010a, b, 2012) more so than among currently depressed older adults (e.g., Thompson et al., 2012; Lamers et al., 2018; see also Hamaker et al., 2018). Arguably, people with elevated depressive symptoms who have not (yet) transitioned into clinical depression and/or young people diagnosed with (possibly their first) episode of depression are less likely to be persistently depressed than older adults with clinical depression. Supporting this view, Bean et al. (2020) found that although ruminative inertia was higher among people with higher depressive symptoms, individuals with a higher number of lifetime depressive episodes actually showed lower ruminative inertia. This is consistent with the proposal that emotional inertia represents an “early warning signal” of an imminent transition from a healthy to a depressed state, or vice versa (Van de Leemput et al., 2014). This proposal, which we discuss in more detail in Sect. 4.6.1 below, derives from a dynamical systems perspective on affective functioning. Specifically, conceiving of affect as a dynamical system implies that there may be multiple stable states (e.g., “healthy” and “depressed”) and that the dynamical properties of affect (e.g., inertia) serve as an indicator of the overall stability/fragility of the system; i.e., how likely the system is to tip from one stable state into another (Scheffer et al., 2018).

4.3.1.5 Inertia as a Marker of Depression Vulnerability

In line with the above reasoning, and replicating earlier research (Kuppens et al., 2010a, b; Suls et al., 1998), several recent studies have linked higher NA inertia with well-known depression vulnerability factors, including habitual rumination, neuroticism, stress, and low or mood-reactive self-esteem. For instance, Brose et al. (2015) reported a positive association between habitual rumination and NA inertia and showed that both uniquely predict depressive symptoms, replicating Koval et al.'s (2012) findings. Two other recent studies (Koval et al., 2016; Waugh et al., 2017) reported that both PA and NA inertia were positively associated with trait rumination and neuroticism. Regarding stress, Wang et al. (2020) showed that individuals reporting higher levels of perceived stress had heightened NA inertia in daily life; and De Longis et al. (2021) reported that emotional exhaustion in response to daily hassles (a component of "burnout") was positively related to emotional inertia. Across two studies, Koval et al. (2016) reported that trait self-esteem was inversely related to PA and NA inertia assessed in the lab, conceptually replicating Kuppens et al. (2010a) findings. Finally, Clasen et al. (2015) found that inertia of sadness in daily life was higher among individuals with more mood-reactive self-esteem, a known cognitive risk factor for depression. Thus, taken together, the above studies provide substantial evidence that a range of vulnerability factors for depression are associated with heightened emotional inertia.

4.3.2 Other Forms of Psychopathology

The empirical evidence reviewed above raises the question of whether emotional inertia is uniquely associated with increased vulnerability to depression or, rather, is a marker of various forms of psychological maladjustment. Supporting the latter view, Houben et al. (2015) found that emotional inertia showed similarly strong associations with a variety of psychological functioning indicators, including measures of negative emotionality, distress and psychopathology, as well as measures of positive emotionality, satisfaction with life and eudaimonic well-being. Houben et al.'s (2015) findings have been corroborated by other recent studies (e.g., Santagelo et al., 2014, 2016), suggesting that emotional inertia is probably not uniquely characteristic of any specific form of psychopathology or dysfunction, but may instead be an indicator of general maladjustment or a transdiagnostic vulnerability factor. However, more recent research suggests that emotional inertia may be differentially associated with higher-order dimensions of psychopathology, such as externalizing and internalizing disorders (Scott et al., 2020). Similarly, heightened inertia of some discrete emotions may be characteristic of more specific psychological disorders. For instance, in a study comparing participants from three clinical groups with healthy controls, Mneimne et al. (2018) reported that greater inertia of shame was specific to borderline personality disorder, whereas inertia of irritability was higher among all clinical groups relative to controls. Such differences would not be detected in studies examining inertia of broader affective dimensions, such as NA and PA.

4.3.2.1 Psychosis

Other recent studies have examined emotional inertia in relation to specific symptom clusters within a clinical diagnostic category. For instance, Westermann et al. (2017) examined how inertia (operationalized using a so-called *attractor strength* parameter, the inverse of inertia) correlates with positive and negative psychosis symptoms. These authors found that while severity of positive symptoms (e.g., hallucinations, delusions) was associated with higher emotional inertia, the opposite was true for negative symptoms (e.g., withdrawal, blunted affect), which showed a negative correlation with inertia. Westermann et al. (2017) interpreted these findings as suggesting that negative symptoms could stem from over-regulation of emotions, which may undermine the adaptive function of emotions and lead to the amotivation observed in negative psychotic symptoms.

4.3.2.2 Borderline Personality Disorder

In relation to BPD, typically characterized by increased instability across multiple psychological domains, Ebner-Priemer et al. (2015) examined differences in inertia between BPD patients and healthy controls across three studies and found evidence that BPD patients show higher inertia, but these results were not consistent across data sets or analytic methods (see also Houben & Kuppens, 2020). Relatedly, Bresin (2014) compared levels of day-to-day PA and NA inertia in daily life among college undergraduates with and without a history of non-suicidal self-injury (NSSI)—a relatively prevalent behavior among individuals with BPD— and found no group difference in NA inertia but significantly lower PA inertia among the NSSI group.

4.3.2.3 Post-traumatic Stress Disorder

Emotional inertia has also recently been investigated in relation to symptoms of post-traumatic stress disorder (PTSD) and distress tolerance. In a sample of US war veterans, Simons et al. (2020) found that individuals with higher distress tolerance (a factor associated with enhanced PTSD recovery) showed lower NA inertia in daily life.

4.3.2.4 Eating Disorders

Finally, two recent studies extended emotional inertia into the field of eating disorders. Williams-Kerver et al. (2020) examined PA and NA inertia among participants with anorexia nervosa, bulimia nervosa and binge-eating disorder, and found that

NA inertia was higher among individuals with bulimia than among those with binge-eating, although no healthy control group was included limiting the inferences that can be drawn from this study. Relatedly, Fuller-Tyszmiewicz et al. (2018) examined how eating disorder symptoms were related to the inertia of body dissatisfaction in daily life, but found no reliable association between either eating disorder symptoms or trait body dissatisfaction and body dissatisfaction inertia.

4.3.3 Personality, Demographics and Other Individual Differences

In addition to research describing relations among emotional inertia and indicators of psychological functioning and well-being, several recent studies have investigated how other dimensions of individual differences, including personality and demographic factors, correlate with emotional inertia.

4.3.3.1 Big Five Personality Traits

As mentioned earlier, Koval et al. (2016) and Waugh et al. (2017) reported positive correlations between neuroticism and emotional inertia, consistent with Suls et al. (1998). These findings were corroborated in a study by Pavani et al. (2017) who also reported that extraversion correlated with lower NA and PA inertia in daily life, consistent with Houben et al.'s (2015) meta-analysis. However, these associations have not been consistently observed, particularly in studies where some attempt is made to correct for overlap of inertia with mean levels and/or other dynamic indices. For instance, when controlling for mean and SD of PA and NA, Koval et al. (2016) found no reliable associations between extraversion and inertia, and Wendt et al. (2020) reported no systematic correlations among any of the Big Five personality dimensions and emotional inertia.

4.3.3.2 Age

Despite a rich and varied literature on age-related differences in emotional functioning (e.g., Charles & Carstensen, 2010), surprisingly few studies have specifically examined age differences in emotional inertia. Consistent with research demonstrating age-related improvements in emotional well-being, Hamaker et al. (2018) found that older adults had lower NA inertia but higher PA inertia than younger adults in a study assessing day-to-day persistence of self-reported feelings. However, these age differences in emotional inertia were not replicated in two recent studies by Wang et al. (2020) and Le Vigouroux et al. (2020), both of whom reported no age-related differences in emotional inertia.

4.3.3.3 Gender

Similar to age differences, there is a dearth of research examining gender differences in emotional inertia. However, some evidence suggests that gender differences in inertia may exist or that gender may moderate associations between inertia and other outcomes. For instance, gender was found to moderate the association between depression and PA inertia, such that PA inertia was higher among depressed versus healthy women, but this was not the case for men (Nelson et al., 2020). Simons et al. (2017) found that drinking alcohol led to decreases in NA inertia only among women but not men, suggesting that women with heightened inertia may be at greater risk of developing alcohol use disorder as their drinking may be reinforced by decreasing the persistence of NA.

4.3.3.4 Relationship Factors

Somers et al. (2020) investigated the association between individual differences in attachment style and inertia of daily PA and feelings of emotional closeness among mothers of young children. They found that avoidant attachment was associated with higher inertia of PA, but with lower inertia of emotional closeness, implying that more avoidantly attached mothers showed more persistence in their PA and less persistence in their feelings of emotional closeness with their children. These findings are consistent with the characterization of avoidant attachment as reflecting a preference for emotional distance and a tendency to minimize negative emotions and distress. Relatedly, Dworkin et al. (2019) examined the inertia of expressive suppression during interactions among romantic couples and observed that women who used suppression more rigidly (i.e., showed greater inertia of suppression) showed a stronger negative association between suppression of negative emotion and relationship satisfaction.

4.3.3.5 Emotional Intelligence

Finally, a recent study investigated links between emotional intelligence and inertia. Given that emotional intelligence captures individual differences in the ability to perceive, understand and manage one’s own and others’ emotions, MacCann et al. (2020) argued that it may relate to daily emotion dynamics. Although emotional intelligence was related to variability and instability of PA and NA, it showed no reliable associations with emotional inertia in daily life, suggesting that emotional intelligence is primarily associated with differences in exposure and/or reactivity to emotional events rather than differences in the degree to which emotions persist over time.

4.4 Mechanisms Underlying Emotional Inertia

The studies reviewed above catalogue a variety of links between individual differences in emotional inertia and various indicators of *intra*personal (e.g., psychopathology, well-being, personality) and *inter*personal (e.g., attachment style, relationship satisfaction) functioning. However, while they describe the nomological network of emotional inertia as a construct, they can only hint at the potential causal mechanisms underlying inertia. Next, we turn our attention to the relatively small volume of research that has attempted to understand what causes inertia, how inertia can change within individuals, and how it can be modified using various interventions.

4.4.1 Genetic Influences

In light of the link between emotional inertia and vulnerability to depression, Van Roekel et al. (2018) investigated whether a possible genetic risk factor for depression may underlie individual differences in inertia. Specifically, these authors examined the 5-HTTLPR genetic polymorphism in relation to NA inertia and found that carriers of the short-allele, which has been associated with impaired functioning of neural networks involved in down-regulation of negative emotions (Pezawas et al., 2005), showed higher NA inertia in daily life. In contrast, a recent twin study reported that individual differences in NA inertia contained 0% variation due to heritable factors and were instead driven by non-shared (91%) and shared (9%) environmental factors (Zheng & Asbury, 2019). Similarly, this study reported that only 9% of between-person variation in PA inertia was due to heritable (i.e., genetic) factors (Zheng & Asbury, 2019). It is difficult to draw solid conclusions regarding the genetic determinants of inertia based on only two studies, which produced inconsistent findings. However, it seems unlikely that emotional inertia would have no genetic determinants, given that most psychological traits tend to be at least moderately heritable (Plomin et al., 2016). Nevertheless, even if genetic factors do not substantially explain differences in emotional inertia, other more proximal biological factors may play a role.

4.4.2 Physiological Processes

Two recent studies have investigated a more proximal biological mechanism underlying emotional inertia, namely peripheral physiological processes. De Longis et al. (2020) found that heart rate variability, an indicator of self-regulatory capacity, was inversely related with NA inertia in an organizational setting. However, their analyses were based on just six measurement occasions, which may be insufficient to provide reliable estimates of inertia (Wang et al., 2012). De Longis et al.'s (2020) findings contrast with Koval et al. (2013a), who reported no association between HRV and either PA or NA inertia in daily life in an undergraduate student sample. However, whereas De Longis et al. (2020) obtained ambulatory measures of heart rate in daily life over 24 h, Koval et al. (2013a) measured heart rate under resting conditions in the lab. This methodological difference may explain the divergent findings, as previous research has distinguished heart rate variability at rest from changes in heart rate variability following/during emotional events (e.g., Butler et al., 2006; Yaroslavsky et al., 2013). Nevertheless, with only two studies that investigated the link between heart rate variability and inertia of affective experience, it seems too early to conclude how they are related, especially in the absence of a clear mechanism explaining their association.

4.4.3 Neural Processes

Neural processes represent an even more proximal biological mechanism underlying emotional inertia, which have been investigated in two recent fMRI studies. Waugh et al. (2017) investigated how changes in cerebral blood flow in brain regions implicated in the regulation of emotion are associated with emotional inertia in daily life. They found that individuals who had greater activation of the lateral prefrontal cortex during an emotional task in the scanner (suggesting greater recruitment of emotion-regulatory neural networks) showed lower inertia in daily life. Provenzano et al. (2018) conducted a similar study examining how changes in neural activation during a social feedback task in the scanner correlated with emotional inertia in daily life. However, Provenzano et al. (2018) identified different brain regions than Waugh et al. (2017) as correlates of NA inertia in daily life. Thus, while these two studies do not provide consistent evidence regarding which specific brain regions are involved, they support the general rationale of looking for neural correlates of emotional inertia, using a combination of functional neuroimaging and experience sampling methods.

4.4.4 Psychological Processes

Finally, at the most proximal level, a number of studies have sought to understand the psychological processes underlying emotional inertia. Although it is difficult to distinguish emotion generation from emotion regulation (Gross, 2015; Gross & Barrett, 2011), a number of studies have sought to determine the extent to which each is responsible for driving emotional inertia. For instance, Koval et al. (2015a) examined how NA inertia, assessed in response to a standardized sequence of films in the lab and naturalistically in daily life, is related to exposure and reactivity to emotional events (processes involved in emotion generation), versus emotional recovery following events (presumably driven by emotion regulation processes). Across methods and analytic approaches, impaired recovery from negative events was the most consistent correlate of NA inertia. In contrast, exposure and reactivity to events were not consistently associated with inertia (see also Thompson et al., 2012). These findings suggest that inertia is driven primarily by emotion-regulating rather than emotion-generating processes and can be thought of as a measure of regulatory weakness rather than of blunted emotional reactivity (cf. Kuppens et al., 2010a).

Consistent with the above reasoning, Iijima et al. (2018) examined how attentional bias (measured using the dot-probe task) correlated with the dynamics of anxiety in daily life and found that while attentional bias towards negative stimuli was associated with greater anxiety reactivity to daily stressors and greater affective instability, it was not related to emotional recovery from stressors or to emotional inertia levels. Given that rapid attentional allocation is primarily involved in emotion generation, Iijima et al.'s (2018) findings are consistent with the view that inertia is not primarily about altered (i.e., blunted) reactivity to environmental changes or events. Rather, it appears to reflect slower emotional recovery, presumably driven by impaired emotion regulation.

More direct evidence for the role of emotion regulation in NA inertia comes from Koval et al. (2015b), who reported that habitual and experimentally induced expressive suppression was associated with increased inertia of negative emotional behaviors, across two studies. Considered together with studies linking emotional inertia with habitual rumination (Brose et al., 2015; Koval et al., 2012, 2016), this suggests that using normatively ineffective emotion regulation strategies (see e.g., Brans et al., 2013; Webb et al., 2012) is associated with a tendency for negative emotions to persist across time. Finally, these findings dovetail with the evidence, reviewed above, that emotional inertia may be related to genetic (van Roekel et al., 2018), physiological (De Longis et al., 2020) and neural (Waugh et al., 2017) markers of emotion-regulatory capacity. Although the individual findings linking heightened NA inertia with various markers of ineffective emotion regulation await replication, taken together these diverse findings suggest that emotional inertia may be driven by difficulties in down-regulating or disengaging from negative emotional states.

4.5 Interventions to Modify Emotional Inertia

If emotional inertia is driven by impaired emotion regulation processes, as we have proposed, interventions that improve the efficacy of emotion regulation or facilitate emotional disengagement may reduce inertia. Below, we discuss a number of studies that support this view.

4.5.1 Mindfulness

Mindfulness is thought to improve emotion regulation by decreasing cognitive over-engagement in response to unpleasant emotional experiences (i.e. worry, rumination) and increasing acceptance of unpleasant experiences (Guendelman et al., 2017). As such, a number of recent studies have explored how mindfulness relates to emotional inertia and other indices of affect dynamics. In line with the proposal that mindfulness is associated with more efficient emotion regulation, Keng and Tong (2016) found that individuals with higher dispositional mindfulness scores had lower NA inertia in daily life. Rowland et al. (2020) replicated this finding, reporting a negative correlation between dispositional mindfulness and inertia of low-arousal NA. Rowland et al. (2020) extended upon Keng and Tong's (2016) study by examining whether a 6-week mindfulness intervention could reduce inertia. They reported a decrease in low-arousal NA (sadness/depression) inertia among participants randomized to the mindfulness intervention, compared with controls. Xu et al. (2015) reported a similar effect of mindfulness training on NA inertia, but only among individuals low in trait mindfulness.

However, some evidence suggests that while mindfulness may be associated with reduced NA inertia, it may actually predict higher inertia of positive emotions, particularly feelings associated with meditative practice such as calmness and compassion. For instance, Rowland et al. (2020) reported that state mindfulness was associated with greater moment-to-moment persistence in low-arousal PA (i.e., feelings of relaxation and satisfaction). Similarly, Tong (2017) found that individuals higher on a measure of daily spirituality had higher inertia of transcendental positive emotions (e.g., compassion, gratitude), although this was only evident when examining day-to-day inertia and not at a shorter (within-day) timescale. Given that PA inertia is less strongly associated with poor functioning than NA inertia (Houben et al., 2015) and a handful of studies have linked higher PA inertia with beneficial outcomes (Hohn et al., 2013; Poerio et al., 2016; Scott et al., 2020), it may be too early to conclude that emotional inertia, per se, is universally maladaptive.

Overall, research on the effects of mindfulness on emotional inertia provides preliminary evidence that it may be a promising intervention for reducing NA inertia, but may also increase PA inertia, particularly for low-arousal positive states.

4.5.2 Exercise and Alcohol

Two other interventions that have been examined in relation to inertia are physical exercise and alcohol consumption. Despite their differences, doing exercise and drinking alcohol may both impact emotional inertia by interrupting perseverative cognition, such as rumination (Fairbairn & Sayette, 2013; Simons et al., 2017). Regarding exercise, Bernstein et al. (2019) found that individuals who reported engaging in more physical exercise over seven days had lower levels of anxiety inertia in daily life. Similarly, another recent study found that individuals who were more physically active (measured using a wrist-worn activity monitor) showed lower NA inertia (Wen et al., 2020). While these results are compelling, experimental evidence of the causal impact of exercise on emotional inertia is still lacking.

In relation to alcohol, Fairbairn and Sayette (2013) used an experimental paradigm to demonstrate that alcohol consumption decreases PA inertia in a naturalistic lab setting. This finding has been replicated recently using an experience sampling design and for NA inertia (Simons et al., 2017), although in the latter study the effect of alcohol on inertia was moderated by gender and by habitual rumination. Thus, despite its potential to reduce the persistence of emotions, alcohol may be more effective in reducing inertia for some individuals than others.

4.6 Within-Person Changes in Emotional Inertia

Research on emotional inertia, and on affect dynamics more broadly, involves identifying "the trajectories, patterns, and regularities with which emotions... fluctuate across time" (Kuppens & Verduyn, 2015, p. 72). Given this explicit concern with temporal dynamics, it is perhaps ironic that most empirical studies to date have (implicitly) assumed that emotional inertia is itself a stable, trait-like characteristic of individuals. Put otherwise, researchers have thus far primarily investigated between-person differences in emotional inertia without considering that inertia may vary *within* individuals. As we have reviewed above, research examining such (presumably) stable individual differences in emotional inertia has yielded important insights into how inertia relates to psychological functioning and well-being, as well as pointing to potential mechanisms underlying between-person differences in inertia. However, the possibility of intraindividual variation in emotional inertia may moderate such between-person effects has so far received far less attention (cf. Koval & Kuppens, 2012; Bringmann et al., 2017).

4.6.1 Application of Dynamical Systems Theory

Applying the principles of dynamical systems theory, researchers are increasingly recognising that both normal and pathological emotional functioning can be characterized as emerging from interactions among affective states and contextual variables, which constitute elements in a complex system (Lewis, 2005; Loossens et al., 2020; B. Nelson et al., 2017; Van de Leemput et al., 2014; Wichers et al., 2015; Witherington & Crichton, 2007). This perspective assumes that how an individual's affect fluctuates over time, including their level of emotional inertia, can change either abruptly (e.g., Cabrieto et al., 2018; Hamaker et al., 2016) or gradually (e.g., Bringmann et al., 2017) across time and/or in different contexts (e.g., Koval & Kuppens, 2012).

4.6.1.1 Inertia as a Marker of Critical Slowing Down

Indeed, research on critical transitions in complex systems has shown that increases in autocorrelation (i.e., inertia) within a dynamical system are an indicator of "critical slowing down", a phenomenon shown to precede transitions between alternate stable states of the system (Scheffer et al., 2009, 2018). A system characterized by high levels of autocorrelation, or inertia, can be described as low in resilience. In a low-resilience system, recovery from even small perturbations is slow and such perturbations are more likely to knock the system into an alternate state, indicating that the system is close to a "tipping point" (Scheffer et al., 2018). Applying this reasoning to the affective system, researchers have proposed that increases in emotional inertia may precede transitions between normal and pathological (e.g., depressed) states, and may therefore represent an early warning signal of imminent changes in emotional health (Van de Leemput et al., 2014). In an influential study, van de Leemput et al. (2014) reported that higher emotional inertia predicted an increased likelihood of a future transition into clinical depression among healthy adults (see also Kuppens et al., 2012), but that higher inertia conversely predicted a greater chance of recovery among depressed individuals (see also Höhn et al., 2013).

However, this study was criticized for not demonstrating within-person changes in emotional inertia preceding transitions between healthy and depressed states (Bos & de Jonge, 2014). In fact, perhaps the earliest study of emotional inertia, by Huba et al. (1976), reported evidence of within-person decreases in emotional inertia among 10 psychiatric inpatients during periods of more severe depression, suggesting that higher inertia may be a signal of imminent recovery among depressed individuals. More recent studies have also provided evidence of within-person changes in emotional inertia preceding transitions in mental health (e.g., Schreuder et al., 2020; Wichers et al., 2016, 2020). However, other studies have failed to find that inertia represents an early warning signal of transitions in emotional functioning (Slofstra et al., 2018). Moreover, a recent paper calls into question whether the phenomenon of critical slowing down (including increases in emotional inertia) is reliably associated with critical transitions between alternate states within dynamic systems (Dablander et al., 2020).

Thus, although it may be too early to conclude that changes in emotional inertia within individuals precede qualitative shifts in their emotional functioning and mental health, this is clearly an important area of growth for the field. To facilitate further research on this issue, a number of recent statistical developments enable the modelling of within-person changes in emotional inertia across contexts and time (e.g., Albers & Bringmann, 2020; Asparouhov et al., 2018; Cabrieto et al., 2018; de Haan-Rietdijk et al., 2016), allowing researchers to move beyond the assumption that inertia represents a stable dispositional characteristic. Applying these newly developed models will be increasingly important to understand not only how emotional inertia changes as a function of various contextual factors, but also how such intraindividual shifts in emotional inertia alter its associations with well-being and functioning (cf. Koval & Kuppens, 2012).

4.7 Open Questions and Future Directions

A great deal has been learned about emotional inertia over the past two decades. Yet, many issues remain unresolved, providing fertile ground for further research. We conclude our review by briefly discussing what we consider to be the most urgent lingering questions regarding emotional inertia and outlining some promising directions for future research. Many basic questions regarding emotional inertia have not yet been conclusively answered. For instance, do physiological, behavioural and experiential components of emotion exhibit similar degrees of inertia within and between individuals? Are some specific emotions or affective dimensions characterized by greater inertia than others? Is inertia of different components or dimensions of affect, measured at different timescales, driven by the same or different processes? How does emotional inertia change over the lifespan and how is it related to other developmental processes? Are there cultural and/or gender differences in emotional inertia? And so forth. Here, we focus on two substantive questions and one methodological question, which we believe are important to advance research on emotional inertia.

4.7.1 Is Emotional Inertia Merely a Surface Phenomenon?

Despite all we have learned about emotional inertia, it remains unclear what it actually is, beyond a statistical model parameter (i.e., an AR slope). As reviewed above, a number of studies have explored potential causal factors underlying emotional inertia, ranging from genetic factors through peripheral physiology to neural activation and other, more basic, psychological processes. Yet, a definitive explanation of what causes or underlies the differences in emotional inertia we observe remains elusive. This brings to mind the distinction between *descriptive* and *explanatory* aspects of personality traits proposed in two prominent theoretical accounts of the Big Five (DeYoung, 2015; Fleeson & Jayawickreme, 2015). At a descriptive level, emotional inertia represents a propensity for emotions to linger or persist across time, reflecting slower recovery from emotional perturbations (Cook et al., 1995; Hamaker, 2012; Jongerling et al., 2015; Koval et al., 2015a). However, why emotions appear to be self-predictable for some individuals and/or in some contexts remains unknown.

We and others have suggested that impairments or dysfunction in emotion regulation processes are at play (e.g., Koval et al., 2015a, b; Suls & Martin, 2005). But conclusive evidence supporting this proposal is still lacking. At this stage, we understand emotional inertia predominantly as a descriptive feature of affect dynamics, whereas the explanatory component of inertia remains underspecified. Put otherwise, the basic building blocks underlying emotional inertia are yet to be determined. Emotional inertia is not unique in this regard: the explanatory mechanisms driving many psychological constructs remain understudied (e.g., Borghi & Fini, 2019). As such, seeking to understand the processes that cause emotional inertia is surely an important direction for future research.

4.7.2 (When) Is Emotional Inertia Maladaptive?

From the outset, emotional inertia has been conceptualised as an indicator of maladjustment (e.g., Cook et al., 1995; Kuppens et al., 2010a; Suls et al., 1998). Yet, evidence that emotional inertia is not necessarily stable, but can vary within individuals, suggests that the question "is inertia maladaptive?" should be replaced with "when is emotional inertia maladaptive?". And one interesting suggestion, which is yet to receive sufficient empirical attention, is that the extent to which emotional inertia is maladaptive may depend on emotional intensity. For instance, Jenkins et al. (2020) found that the positive association between NA inertia and depressive symptoms decreased at higher mean levels of NA, aligning with Koval and Kuppens' (2012) finding that the relationship between depression and NA inertia reverses under stressful conditions. This may be because, among healthy individuals, emotional inertia tends to decrease during more intense episodes of affect/stress, indicating an adaptive increase in regulatory strength or pull-back towards affective equilibrium under stress (de Haan-Rietdijk et al., 2016).

We speculate that this tendency for inertia to decrease as a function of emotional intensity may be exaggerated in psychologically maladjusted individuals, leading to over-regulation during periods of intense affect. This proposal coincides with recent evidence of a curvilinear association between emotional inertia and relationship quality, such that a moderate level of inertia was associated with optimal relationship functioning (Luginbuehl & Schoebi, 2020). Yet, although the suggestion that there may be an optimal level of emotional inertia has intuitive and theoretical appeal (cf. Hollenstein et al., 2013), definitive evidence for this proposition has not yet been found. Thus, we argue that understanding the circumstances under which differing levels of emotional inertia may be more/less (mal)adaptive is crucial to developing a comprehensive understanding of affect dynamics.

4.7.3 Towards a Standard Modelling Approach

Finally, given recent challenges to the reliability of emotional inertia as an index of affect dynamics (Wendt et al., 2020) and its unique predictive validity for well-being (Dejonckheere et al., 2019), it seems increasingly important to develop consensus on a standard modelling approach for operationalizing the construct of emotional inertia. However, several questions regarding how to model emotional inertia–which we have discussed in the current review–remain unresolved. For example, which other parameters should be included in AR(1) models used to quantify inertia? Should such models necessarily partition within-person dynamic variation in affect into predictable (autoregressive) and unpredictable (innovation variance) components? Equally, should longer-term trends and/or measurement error always be accounted for when modelling inertia? Should continuous or discrete time models be used, and when can they be considered practically equivalent? Should researchers always control for covariance between inertia and other affect dynamic parameters when examining associations with outcomes of interest? Given that PA and NA are, for most individuals, non-independent at the within-person level (Dejonckheere et al., 2019), should PA and NA dynamics be modelled simultaneously, accounting for their mutual influences? And last, but certainly not least, how confident can we be that our statistical models accurately represent the true processes driving affect dynamics?

To paraphrase George Box, while all models may be fundamentally wrong, some models are more useful than others (Wasserstein, 2010). How do we identify which models are most useful for quantifying affect dynamics? A crucial step, often skipped by researchers (including, admittedly, ourselves) who rush to investigate how affect dynamics correlate with other outcomes, is to determine how well our statistical models fit observed emotional time-series data (Butler & Barnard, 2019). Thus, we argue that more attention should be given to model fitting, cross-validation and comparison.

4.8 Concluding Remarks

The study of affect dynamics has bloomed over the past couple of decades, as evidenced by the diverse contributions to this edited volume. During this time, research interest in emotional inertia has continued to gain momentum (pun intended). We now know that individuals differ meaningfully in the degree to which their emotions persist over time, and such differences correlate reliably with indicators of psychological functioning and well-being. And yet, the reliability of emotional inertia as an individual difference measure and its incremental validity (over-and-above simpler features of affect, such as mean levels) for predicting well-being have recently been questioned. Evidence that emotional inertia is not exclusively stable/trait-like, but can also vary over time within individuals, suggests that identifying *when* inertia reflects emotional dysregulation/dysfunction will require novel approaches to measuring and modeling emotional fluctuations across a variety of contexts. How emotional inertia is statistically operationalized also has important substantive implications and therefore selecting the right analytic approach and statistical model is crucial. Finally, we believe that the next phase of research on emotional inertia should place greater emphasis on identifying the underlying causal mechanisms that drive both between- and within-person variation in emotional inertia. We call for researchers to move beyond descriptive accounts and strive towards developing an explanatory model of emotion dynamics, which seeks to understand the processes that cause different patterns of emotional fluctuation over time.

References

Albers, C. J., & Bringmann, L. F. (2020). Inspecting gradual and abrupt changes in emotion dynamics with the time-varying change point autoregressive model. *European Journal of Psychology Assessment, 36*(3), 492–499.

Asparouhov, T., Hamaker, E. L., & Muthen, B. (2018). Dynamic structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal, 25*(3), 359–388.

Bean, C. A. L., Heggeness, L. F., Kalmbach, D. A., & Ciesla, J. A. (2020). Ruminative inertia and its association with current severity and lifetime course of depression. *Clinical Psychological Science*. https://doi.org/10.1177/2167702620949174

Bernstein, E. E., Curtiss, J. E., Wu, G. W. Y., Barreira, P. J., & McNally, R. J. (2019). Exercise and emotion dynamics: An experience sampling study. *Emotion (Washington, D.C.), 19*(4), 637–644. https://doi.org/10.1037/emo0000462

Bolger, N., & Laurenceau, J.-P. (2013). Methodology in the social sciences. In *Intensive longitudinal methods: An introduction to diary and experience sampling research*. Guilford Press.

Bos, E. H., & de Jonge, P. (2014). "Critical slowing down in depression" is a great idea that still needs empirical proof. *Proceedings of the National Academy of Sciences of the United States of America, 111*(10), E878.

Bos, E. H., de Jonge, P., & Cox, R. F. A. (2018). Affective variability in depression: Revisiting the inertia-instability paradox. *British Journal of Psychology*. https://doi.org/10.1111/bjop.12372

Bos, E. H., de Jonge, P., & Cox, R. F. A. (2019). Affective variability in depression: Revisiting the inertia-instability paradox. *British Journal of Psychology, 110*(4), 814–827. https://doi.org/10.1111/bjop.12372

Bosley, H. G., Soyster, P. D., & Fisher, A. J. (2019). Affect dynamics as predictors of symptom severity and treatment response in mood and anxiety disorders: Evidence for specificity. *Journal for Person-Oriented Research, 5*(2), 101–113. https://doi.org/10.17505/jpor.2019.09

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2008). *Time series analysis: Forecasting and control*. Wiley.

Brans, K., Koval, P., Verduyn, P., Lim, Y. L., & Kuppens, P. (2013). The regulation of negative and positive affect in daily life. *Emotion, 13*(5), 926–939. https://doi.org/10.1037/a0032400.

Bresin, K. (2014). Five indices of emotion regulation in participants with a history of nonsuicidal self-injury: A daily diary study. *Behaviour Therapy, 45*(1), 56–66. https://doi.org/10.1016/j.beth.2013.09.005

Bringmann, L. F., Hamaker, E. L., Vigo, D. E., Aubert, A., Borsboom, D., & Tuerlinckx, F. (2017). Changing dynamics: Time-varying autoregressive models using generalized additive modeling. *Psychological Methods, 22*(3), 409–425. https://doi.org/10.1037/met0000085

Borghi, A. M., & Fini, C. (2019). Theories and explanations in psychology. *Frontiers in Psychology, 10*, 958.

Brose, A., Schmiedek, F., Koval, P., & Kuppens, P. (2015). Emotional inertia contributes to depressive symptoms beyond perseverative thinking. *Cognition and Emotion, 29*(3), 527–538. https://doi.org/10.1080/02699931.2014.916252

Butler, E. A., & Barnard, K. J. (2019). Quantifying interpersonal dynamics for studying socio-emotional processes and adverse health behaviors. *Psychosomatic Medicine, 81*(8), 749–758. https://doi.org/10.1097/PSY.0000000000000703

Butler, E. A., Wilhelm, F. H., & Gross, J. J. (2006). Respiratory sinus arrhythmia, emotion, and emotion regulation during social interaction. *Psychophysiology, 43*(6), 612–622.

Cabrieto, J., Adolf, J., Tuerlinckx, F., Kuppens, P., Ceulemans, E., & R. P. P. (2018). Detecting long-lived autodependency changes in a multivariate system via change point detection and regime switching models. *Scientific Reports, 8*(1), 15637.

Charles, S. T., & Carstensen, L. L. (2010). Social and emotional aging. *Annual Review of Psychology, 61*, 383–409.

Clasen, P., Fisher, A. J., & Beever, C. (2015). Mood-reactive self-esteem and depression vulnerability: Person-specific symptom dynamics via smart phone assessment. *PLoS One, 10*(7), e0129774. https://doi.org/10.1371/journal.pone.0129774

Cook, J., Tyson, R., White, J., Rushe, R., Gottman, J., & Murray, J. (1995). Mathematics of marital conflict: Qualitative dynamic mathematical modeling of marital interaction. *Journal of Family Psychology, 9*(2), 110–130.

Dablander, F., Pichler, A., Cika, A., & Bacilieri, A. (2020). Anticipating critical transitions in psychological systems using early warning signals: Theoretical and practical considerations. *Theoretical and Practical Considerations*. https://doi.org/10.31234/osf.io/5wc28

de Haan-Rietdijk, S., Gottman, J. M., Bergeman, C. S., & Hamaker, E. L. (2016). Get over it! A multilevel threshold autoregressive model for state-dependent affect regulation. *Psychometrika, 81*(1), 217–241. https://doi.org/10.1007/s11336-014-9417

De Haan-Rietdijk, S., Voelkle, M. C., Keijsers, L., & Hamaker, E. L. (2017). Discrete- vs. continuous-time modeling of unequally spaced experience sampling method data. *Frontiers in Psychology, 8*(1849).

De Longis, E., Alessandri, G., & Ottaviani, C. (2020). Inertia of emotions and inertia of the heart: Physiological processes underlying inertia of negative emotions at work. *International Journal of Psychophysiology, 155*, 210–218.

De Longis, E., Alessandri, G., Sonnentag, S., & Kuppens, P. (2021). Inertia of negative emotions at work: Correlates of inflexible emotion dynamics in the workplace. Applied Psychology. https://doi.org/10.1111/apps.12325

Dejonckheere, E., Mestdagh, M., Houben, M., Rutten, I., Sels, L., Kuppens, P., & Tuerlinckx, F. (2019). Complex affect dynamics add limited information to the prediction of psychological well-being. *Natural Human Behaviour, 3*(5), 478–491. https://doi.org/10.1038/s41562-019-0555-0

DeYoung, C. G. (2015). Cybernetic big five theory. *Journal of Research in Personality, 56*, 33–58. https://doi.org/10.1016/j.jrp.2014.07.004

Dworkin, J. D., Zimmerman, V., Waldinger, R. J., & Schulz, M. S. (2019). Capturing naturally occurring emotional suppression as it unfolds in couple interactions. *Emotion, 19*(7), 1224–1235. https://doi.org/10.1037/emo0000524

Ebner-Priemer, U. W., Houben, M., Santagelo, P., Kleindienst, N., Tuerlinckx, F., Oravecz, Z., Verleysen, G., Van Deun, K., Bohus, M., & Kuppens, P. (2015). Unraveling affective dysregulation in borderline personality disorder: A theoretical model and empirical evidence. *Journal of Abnormal Psychology, 124*(1), 186–198. https://doi.org/10.1037/abn0000021

Emler, T., Geschwind, N., Peeters, F., Wichers, M., & Bringmann, L. (2020). Getting stuck in social isolation: Solitude inertia and depressive symptoms. *Journal of Abnormal Psychology, 129*(7), 713–723. https://doi.org/10.1037/abn0000588

Fairbairn, C. E., & Sayette, M. A. (2013). The effect of alcohol on emotional inertia: A test of alcohol myopia. *Journal of Abnormal Psychology, 122*(3), 770–781. https://doi.org/10.1037/a0032980

Fleeson, W., & Jayawickreme, E. (2015). Whole trait theory. *Journal of Research in Personality, 56*, 82–92. https://doi.org/10.1016/j.jrp.2014.10.009

Frijda, N. H. (1988). The laws of emotion. *The American Psychologist, 43*(5), 349–358.

Frijda, N. H. (2007). *The laws of emotion*. Lawrence Erlbaum Associates.

Fuller-Tyszmiewicz, M., Richardson, B., Lewis, V., Smyth, J., & Krug, I. (2018). Do women with greater trait body dissatisfaction experience body dissatisfaction states differently? An experience sampling study. *Body Image, 25*, 1–8. https://doi.org/10.1016/j.bodyim.2018.01.004

Gilbert, K. E., Tonge, N. A., & Thompson, R. J. (2019). Associations between depression, anxious arousal and manifestations of psychological inflexibility. *Journal of Behavior Therapy and Experimental Psychiatry, 62*, 88–96. https://doi.org/10.1016/j.jbtep.2018.09.006

Gottman, J. M. (1981). Time-series analysis: A comprehensive introduction for social scientists. *Journal of Forecasting, 1*(3), 94–95. https://doi.org/10.1002/for.3980030114

Gottman, J. M., McFall, R. M., & Barnett, J. T. (1969). Design and analysis of research using time series. *Psychological Bulletin, 72*(4), 299. https://doi.org/10.1037/h0028021

Gottman, J., Swanson, C., & Swanson, K. (2002). A general systems theory of marriage: Nonlinear difference equation modeling of marital interaction. *Personality and Social Psychology Review, 6*(4), 326–340.

Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological Inquiry, 26*(1), 1–26. https://doi.org/10.1080/1047840X.2014.940781

Gross, J. J., & Barrett, L. F. (2011). Emotion generation and emotion regulation: One or two depends on your point of view. *Emotion Review, 3*(1), 8–16. https://doi.org/10.1177/1754073910380974

Gruber, J., Kogan, A., Quoidbach, J., & Mauss, I. B. (2013). Happiness is best kept stable: Positive emotion variability is associated with poorer psychological health. *Emotion, 13*(1), 1–6.

Guendelman, S., Medeiros, S., & Rampes, H. (2017). Mindfulness and emotion regulation: Insights from neurobiological, psychological, and clinical studies. *Frontiers in Psychology, 8*, 220. https://doi.org/10.3389/fpsyg.2017.00220

Hamaker, E. L. (2012). Why researchers should think "within-person": A paradigmatic rationale. In *Handbook of research methods for studying daily life* (pp. 43–61). The Guilford Press.

Hamaker, E. L., Asparouhov, T., Brose, A., Schmiedek, F., & Muthen, B. (2018). At the frontiers of modeling intensive longitudinal data: Dynamic structural equation models for the affective measurements from the COGITO study. *Multivariate Behavioral Research, 53*(6), 820–841.

Hamaker, E. L., & Grasman, R. P. P. P. (2015). To center or not to center? Investigating inertia with a multilevel autoregressive model. *Frontiers in Psychology, 5*. https://doi.org/10.3389/fpsyg.2014.01492

Hamaker, E. L., Grasman, R. P. P. P., & Kamphuis, J. H. (2016). Modeling BAS dysregulation in bipolar disorder. *Assessment, 23*(4), 436–446.

Heininga, V. E., Dejonckheere, E., & Houben, M. (2019). The dynamical signature of anhedonia in major depressive disorder: Positive emotion dynamics, reactivity, and recovery. *BMC Psychiatry, 19*(59). https://doi.org/10.1186/s12888-018-1983-5

Heininga, V. E., Van Roekel, E., Ahles, J. J., Oldehinkel, A. J., & Mezulis, A. H. (2017). Positive affective functioning in anhedonic individuals' daily life: Anything but flat and blunted. *Journal of Affective Disorders, 218*, 437–445. https://doi.org/10.1016/j.jad.2017.04.029

Heller, A. S., Fox, A. S., & Davidson, R. J. (2018). Parsing affective dynamics to identify risk for mood and anxiety disorders. *Emotion*. https://doi.org/10.1037/emo0000440

Höhn, P., Menne-Lothmann, C., Peeters, F., Nicolson, N. A., Jacobs, N., Derom, C., Thiery, E., van Os, J., & Wichers, M. (2013). Moment-to-moment transfer of positive emotions in daily life predicts future course of depression in both general population and patient samples. *PLoS One, 8*(9), e75655. https://doi.org/10.1371/journal.pone.0075655

Hollenstein, T., Lichtwarck-Aschoff, A., & Potworowski, G. (2013). A model of socioemotional flexibility at three time scales. *Emotion Review, 5*(4), 397–405. https://doi.org/10.1177/1754073913484181

Houben, M., Van Den Noortgate, W., & Kuppens, P. (2015). The relation between short-term emotion dynamics and psychological well-being: A meta-analysis. *Psychological Bulletin, 141*(4), 901–930. https://doi.org/10.1037/a0038822

Houben, M., & Kuppens, P. (2020). Emotion dynamics and the association with depressive features and borderline personality disorder traits: Unique, specific, and prospective relationships. *Clinical Psychological Science, 8*(2), 226–239. https://doi.org/10.1177/2167702619871962

Huba, G. J., Lawlor, W. G., Stallone, F., & Fieve, R. R. (1976). The use of autocorrelation analysis in the longitudinal study of mood patterns in depressed patients. *The British Journal of Psychiatry: the Journal of Mental Science, 128*, 146–155.

Iijima, Y., Takano, K., & Tanno, Y. (2018). Attentional bias and its association with anxious mood dynamics. *Emotion, 18*(5), 725–735. https://doi.org/10.1037/Emo0000338

Jahng, S., Wood, P. K., & Trull, T. J. (2008). Analysis of affective instability in ecological momentary assessment: Indices using successive difference and group comparison via multilevel modeling. *Psychological Methods, 13*(4), 354–375. https://doi.org/10.1037/a0014173

Jenkins, B. N., Hunter, J. F., Richardson, M. J., Conner, T. S., & Pressman, S. D. (2020). Affect variability and predictability: Using recurrence quantification analysis to better understand how the dynamics of affect relate to health. *Emotion, 20*(3), 391–402. https://doi.org/10.1037/emo0000556

Jongerling, J., Laurenceau, J.-P., & Hamaker, E. L. (2015). A multilevel AR(1) model: Allowing for inter-individual differences in trait-scores, inertia, and innovation variance. *Multivariate Behavioral Research, 50*(3), 334–349. https://doi.org/10.1080/00273171.2014.1003772

Kashdan, T. B., & Rottenberg, J. (2010). Psychological flexibility as a fundamental aspect of health. *Clinical Psychology Review, 30*(7), 865–878.

Keng, S.-L., & Tong, E. M. W. (2016). Riding the tide of emotions with mindfulness: Mindfulness, affect dynamics, and the mediating role of coping. *Emotion, 16*(5), 706–718. https://doi.org/10.1037/emo0000165

Koval, P., Brose, A., Pe, M. L., Houben, M., Erbas, Y., Champagne, D., & Kuppens, P. (2015a). Emotional inertia and external events: The roles of exposure, reactivity, and recovery. *Emotion, 15*(5), 625–636. https://doi.org/10.1037/emo0000059

Koval, P., Butler, E. A., Hollenstein, T., Lanteigne, D., & Kuppens, P. (2015b). Emotion regulation and the temporal dynamics of emotions: Effects of cognitive reappraisal and expressive suppression on emotional inertia. *Cognition and Emotion, 29*(5), 831–851. https://doi.org/10.1080/02699931.2014.948388

Koval, P., & Kuppens, P. (2012). Changing emotion dynamics: Individual differences in the effect of anticipatory social stress on emotional inertia. *Emotion, 12*(2), 256–267. https://doi.org/10.1037/a0024756

Koval, P., Kuppens, P., Allen, N. B., & Sheeber, L. (2012). Getting stuck in depression: The roles of rumination and emotional inertia. *Cognition and Emotion, 26*(8), 1412–1427. https://doi.org/10.1080/02699931.2012.667392

Koval, P., Ogrinz, B., Kuppens, P., Van den Bergh, O., Tuerlinckx, F., & Sutterlin, S. (2013a). Affective instability in daily life is predicted by resting heart rate variability. *PLoS One, 8*(11), e81536. https://doi.org/10.1371/journal.pone.0081536

Koval, P., Pe, M. L., Meers, K., & Kuppens, P. (2013b). Affect dynamics in relation to depressive symptoms: Variable, unstable or inert? *Emotion, 13*(6), 1132–1141. https://doi.org/10.1037/a0033579

Koval, P., Sütterlin, S., & Kuppens, P. (2016). Emotional inertia is associated with lower well-being when controlling for differences in emotional context. *Frontiers in Psychology, 6*, 1997. https://doi.org/10.3389/fpsyg.2015.01997

Krone, T., Albers, C. J., Kuppens, P., & Timmerman, M. E. (2018). A multivariate statistical model for emotion dynamics. *Emotion, 18*(5), 739–754. https://doi.org/10.1037/emo0000384

Krzysztofowicz, R., & Evans, W. B. (2008). The role of climate autocorrelation in probablistic forecasting. *Monthly Weather Review, 136*(12), 4572–4592. https://doi.org/10.1175/2008MWR2375.1

Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010a). Emotional inertia and psychological maladjustment. *Psychological Science, 21*(7), 984–991. https://doi.org/10.1177/0956797610372634

Kuppens, P., Oravecz, Z., & Tuerlinckx, F. (2010b). Feelings change: Accounting for individual differences in the temporal dynamics of affect. *Journal of Personality and Social Psychology, 99*(6), 1042–1060. https://doi.org/10.1037/a0020962

Kuppens, P., Sheeber, L. B., Yap, M. B. H., Whittle, S., Simmons, J. G., & Allen, N. B. (2012). Emotional inertia prospectively predicts the onset of depressive disorder in adolescence. *Emotion, 12*(2), 283–289. https://doi.org/10.1037/a0025046

Kuppens, P. (2015). It's about time: A special section on affect dynamics. Emotion Review, 7(4), 297–300. http://journals.sagepub.com/doi/abs/10.1177/1754073915590947

Kuppens, P., & Verduyn, P. (2015). Looking at emotion regulation through the window of emotion dynamics. *Psychological Inquiry, 26*(1), 72–79.

Kuppens, P., & Verduyn, P. (2017). Emotion dynamics. *Current Opinion in Psychology, 17*, 22–26. https://doi.org/10.1016/j.copsyc.2017.06.004

Lamers, F., Swendsen, J., Cui, L., Husky, M., Johns, J., Zipunnikov, V., & Merikangas, K. R. (2018). Mood reactivity and affective dynamics in mood and anxiety disorders. *Journal of Abnormal Psychology, 127*(7), 659–669. https://doi.org/10.1037/abn0000378

Le Vigouroux, S., Dauvier, B., & Congard, A. (2020). Development of affect and affective stability in adulthood: Nonlinear age-related differences in daily life. *Current Psychology*. https://doi.org/10.1007/s12144-020-00743-y

Lewis, M. D. (2005). Bridging emotion theory and neurobiology through dynamic systems modeling. *The Behavioral and Brain Sciences, 28*(2), 169–194, 194–245.

Loossens, T., Mestdagh, M., Dejonckheere, E., Kuppens, P., Tuerlinckx, F., & Verdonck, S. (2020). The affective ising model: A computational account of human affect dynamics. *PLoS Computational Biology, 16*(5), e1007860.

Luginbuehl, T., & Schoebi, D. (2020). Emotion dynamics and responsiveness in intimate relationships. *Emotion, 20*(2), 133–148. https://doi.org/10.1037/emo0000540

MacCann, C., Erbas, Y., Dejonckheere, E., Minbashian, A., Kuppens, P., & Fayn, K. (2020). Emotional intelligence relates to emotions, emotion dynamics, and emotion complexity: A meta-analysis and experience sampling study. *European Journal of Psychology Assessment, 36*(3), 460–470. https://doi.org/10.1027/1015-5759/a000588

Mneimne, M., Fleeson, W., Arnold, E. M., & Furr, R. M. (2018). Differentiating the everyday emotion dynamics of borderline personality disorder from major depressive disorder and bipolar disorder. *Personality Disorders: Theory, Research, and Treatment, 9*(2), 192–196. https://doi.org/10.1037/per0000255

Nelson, B., McGorry, P. D., Wichers, M., Wigman, J. T., & Hartmann, J. A. (2017). Moving from static to dynamic models of the onset of mental disorder: A review. *JAMA Psychiatry, 74*, 528–534. https://doi.org/10.1001/jamapsychiatry.2017.0001

Nelson, J., Klumparendt, A., Doebler, P., & Ehring, T. (2020). Everyday emotional dynamics in major depression. *Emotion, 20*(2), 179–191. https://doi.org/10.1037/emo0000541

Ogbaselase, F. A., Mancini, K. J., & Luebbe, A. M. (2020). Indirect effect of family climate on adolescent depression through emotion regulatory processes. *Emotion*. https://doi.org/10.1037/emo0000899

Pavani, J.-B., Vigouroux, S. L., Kop, J.-L., & Congard, A. (2017). A network approach to affect regulation dynamics and personality trait-induced variations: Extraversion and neuroticism moderate reciprocal influences between affect and affect regulation strategies. *European Journal of Personality, 31*, 329–346. https://doi.org/10.1002/per.2109

Pezawas, L., Meyer-Lindenberg, A., Drabant, E. M., Verchinski, B. A., Munoz, K. E., Kolachana, B. S., Egan, M. F., Mattay, V. S., Hariri, A. R., & Weinberger, D. R. (2005). 5-HTTLPR polymorphism impacts human cingulate-amygdala interactions: A genetic susceptibility mechanism for depression. *Nature Neuroscience, 8*(6), 828–834.

Plomin, R., DeFries, J. C., Knopik, V. S., & Neiderhiser, J. M. (2016). Top 10 replicatedfindings from behavioral genetics. *Perspectiveson Psychological Science, 11*, 3–23.

Poerio, G. L., Totterdell, P., Emerson, L. M., & Miles, E. (2016). Social daydreaming and adjustment: An experience-sampling study of socio-emotional adaptation during a life transition. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2016.00013

Provenzano, J., Bastiannsen, J. A., Verduyn, P., Oldehinkel, A. J., Fossati, P., & Kuppens, P. (2018). Different aspects of the neural response to socio-emotional events are related to instability and inertia of emotional experience in daily life: An fMRI-ESM study. *Frontiers in Human Neuroscience, 12*, 501.

Rovine, M. J., & Walls, T. A. (2006). Multilevel autoregressive modeling of interindividual differences in the stability of a process. In *Models for intensive longitudinal data* (pp. 124–147). Oxford University Press.

Rowland, Z., Wenzel, M., & Kubiak, T. (2020). A mind full of happiness: How mindfulness shapes affect dynamics in daily life. *Emotion, 20*(3), 436–451. https://doi.org/10.1037/emo0000562

Santagelo, P., Reinhard, I., Mussgay, L., Steil, R., Sawitzki, G., Klein, C., Trull, T. J., Bonhus, M., & Ebner-Priemer, U. W. (2014). Specificity of affective instability in patients with borderline personality disorder compared to posttraumatic stress disorder, bulimia nervosa, and healthy controls. *Journal of Abnormal Psychology, 123*(1), 258–272. https://doi.org/10.1037/a0035619

Santagelo, P. S., Limberger, M. F., Stiglmayr, C., Houben, M., Coosemans, J., Verleysen, G., Kuppens, P., Tuerlinckx, F., Vanpaemel, W., & Ebner-Priemer, U. W. (2016). Analyzing subcomponents of affective dysregulation in borderline personality disorder in comparison to other clinical groups using multiple e-diary datasets. *Borderline Personality Disorder and Emotion Dysregulation, 3*(1), 5. https://doi.org/10.1186/s40479-016-0039-z

Scheffer, M., Bascompte, J., Brock, W. A., Brovkin, V., Carpenter, S. R., Dako, V., Held, H., van Nes, E. H., Rietkerk, M., & Sugihara, G. (2009). Early-warning signals for critical transitions. *Nature, 461*(7260), 53–59.

Scheffer, M., Bolhuis, J. E., Borsboom, D., Buchman, T. G., Gijzel, S. M. W., Goulson, D., Kammenga, J. E., Kemp, B., Van de Leemput, I. A., Levin, S., Martin, C. M., Melis, R. J. F., van Nes, E. H., Romero, L. M., & Olde Rikkert, M. G. M. (2018). Quantifying resilience of humans and other animals. *Proceedings of the National Academy of Sciences of the United States of America, 115*(47), 11883–11890.

Schreuder, M. J., Hartman, C. A., George, S. V., Menne-Lothmann, C., Decoster, J., van Winkel, R., Delespaul, P., De Hert, M., Derom, C., Thiery, E., Rutten, B. P. F., Jacobs, N., van Os, J., Wigman, J. T. W., & Wichers, M. (2020). Early warning signals in psychopathology: What do they tell? *BMC Medicine, 18*(1), 269.

Schuurman, N. K., & Hamaker, E. L. (2019). Measurement error and person-specific reliability in multilevel autoregressive modeling. *Psychological Methods, 24*(1), 70–91.

Scott, L. N., Victor, S. E., Kaufman, E. A., Beeney, J. E., Byrd, A. L., Vine, V., Pilkonis, P. A., & Stepp, S. D. (2020). Affective dynamics across internalizing and externalizing dimensions of psychopathology. *Clinical Psychological Science, 8*(3), 412–427. https://doi.org/10.1177/2167702619898802

Simons, J. S., Emery, N. N., Simons, R. M., Wills, T. A., & Webb, M. K. (2017). Effects of alcohol, rumination, and gender on the time course of negative affect. *Cognition and Emotion, 31*(7), 1405–1418. https://doi.org/10.1080/02699931.2016.1226162

Simons, J. S., Simons, R. M., Grimm, K. J., Keith, J. A., & Stoltenberg, S. F. (2020). Affective dynamics among veterans: Associations with distress tolerance and posttraumatic stress symptoms. *Emotion*. https://doi.org/10.1037/emo0000745

Slofstra, C., Nauta, M. H., Bringmann, L. F., Klein, N. S., Albers, C. J., Batalas, N., Wichers, M., & Bockting, C. L. H. (2018). Individual negative affective trajectories can be detected during different depressive relapse prevention strategies. *Psychotherapy and Psychosomatics, 87*(4), 243–245.

Somers, J. A., Kerr, M. L., McNeish, D., Smiley, P. A., Buttitta, K. V., Rusmussen, H. F., & Borelli, J. L. (2020). Quantitatively representing real-time emotion dynamics: Attachment-based differences in mothers' emotion experiences. *Journal of Family Psychology, 34*(4), 480–489. https://doi.org/10.1037/fam0000617

Sperry, S. H., Walsh, M. A., & Kwapil, T. R. (2020). Emotion dynamics concurrently and prospectively predict mood psychopathology. *Journal of Affective Disorders, 261*, 67–75. https://doi.org/10.1016/j.jad.2019.09.076

Suls, J., Green, P., & Hillis, S. (1998). Emotional reactivity to everyday problems, affective inertia, and neuroticism. *Personality and Social Psychology Bulletin, 24*(2), 127–136. https://doi.org/10.1177/0146167298242002

Suls, J., & Martin, R. (2005). The daily life of the garden-variety neurotic: Reactivity, stressor exposure, mood spillover, and maladaptive coping. *Journal of Personality, 73*(6), 1485–1509.

Thompson, R. J., Mata, J., Jaeggi, S. M., Buschkuehl, M., Jonides, J., & Gotlib, I. H. (2012). The everyday emotional experience of adults with major depressive disorder: Examining emotional instability, inertia, and reactivity. *Journal of Abnormal Psychology, 121*(4), 819–829. https://doi.org/10.1037/a0027978

Tong, E. M. W. (2017). Spirituality and the temporal dynamics of transcendental positive emotions. *Psychology of Religion and Spirituality, 9*(1), 70–81. https://doi.org/10.1037/rel0000061

Van de Leemput, I. A., Wichers, M., Cramer, A. O. J., Borsboom, D., Tuerlinckx, F., Kuppens, P., van Nes, E. H., Viechtbauer, W., Giltay, E. J., Aggen, S. H., Derom, C., Jacobs, N., Kendler, K. S., van der Maas, H. L. J., Neale, M. C., Peeters, F., Thiery, E., Zachar, P., & Scheffer, M. (2014). Critical slowing down as early warning for the onset and termination of depression. *Proceedings of the National Academy of Sciences of the United States of America, 111*(1), 87–92.

Van Roekel, E., Bennik, E. C., Bastiannsen, J. A., Verhagen, M., Ormel, J., Engels, R. C. M. E., & Oldehinkel, A. J. (2016). Depressive symptoms and the experience of pleasure in daily life: An exploration of associations in early and late adolescence. *Journal of Abnormal Child Psychology, 44*, 999–1009. https://doi.org/10.1007/s10802-015-0090-z

Van Roekel, E., Verhagen, M., Engels, R. C. M. E., & Kuppens, P. (2018). Variation in the serotonin transporter polymorphism (5-HTTLPR) and inertia of negative and positive emotions in daily life. *Emotion, 18*(2), 229–236. https://doi.org/10.1037/emo0000336

Walls, T. A., & Schafer, J. L. (2006). *Models for intensive longitudinal data*. Oxford University Press.

Wang, D., Schneider, S., Schwartz, J. E., & Stone, A. A. (2020). Heightened stress in employed individuals is linked to altered variability and inertia in emotions. *Frontiers in Psychology, 11*, 1152. https://doi.org/10.3389/fpsyg.2020.01152

Wang, L. P., Hamaker, E. L., & Bergeman, C. S. (2012). Investigating inter-individual differences in short-term intra-individual variability. *Psychological Methods, 17*(4), 567–581. https://doi.org/10.1037/a0029317

Wasserstein, R. (2010). George box: A model statistician. *Significance. Statistics Making Sense, 7*(3), 134–135.

Waugh, C. E., Shing, E. Z., Avery, B. M., Jung, Y., Whitlow, C. T., & Maldjian, J. A. (2017). Neural predictors of emotional inertia in daily life. *Social Cognitive and Affective Neuroscience, 12*(9), 1448–1459. https://doi.org/10.1093/scan/nsx071

Webb, T. L., Miles, E., & Sheeran, P. (2012). Dealing with feeling: a meta-analysis of the effectiveness of strategies derived from the process model of emotion regulation. *Psychological Bulletin, 138*(4), 775–808. https://doi.org/10.1037/a0027600

Wen, X., An, Y., Li, W., Du, J., & Xu, W. (2020). How could physical activities and sleep influence affect inertia and affect variability? Evidence based on ecological momentary assessment. *Current Psychology.* https://doi.org/10.1007/s12144-020-00803-3

Wendt, L. P., Wright, A. G. C., Pilkonis, P. A., Woods, W. C., Denissen, J. J. A., Kühnel, A., & Zimmermann, J. (2020). Indicators of affect dynamics: Structure, reliability, and personality correlates. *European Journal of Personality*, 1–13. https://doi.org/10.1002/per.2277

Wenze, S. J., Gunthert, K. C., Forand, N. R., & Laurenceau, J.-P. (2009). The influence of dysphoria on reactivity to naturalistic fluctuations in anger. *Journal of Personality, 77*(3), 795–824.

Westermann, S., Grezellschak, S., Oravecz, Z., Moritz, S., Lüdtke, T., & Jansen, A. (2017). Untangling the complex relationships between symptoms of schizophrenia and emotion dynamics in daily life: Findings from an experience sampling pilot study. *Psychiatry Research, 257*, 514–518. https://doi.org/10.1016/j.psychres.2017.08.023

Wichers, M., Groot, P. C., & Psychosystems, E. G. (2016). Critical slowing down as a personalized early warning signal for depression. *Psychotherapy and Psychosomatics, 85*(2), 114–116.

Wichers, M., Smit, A. C., & Snippe, E. (2020). Early warning signals based on momentary affect dynamics can expose nearby transitions in depression: A confirmatory single-subject time-series study. *Journal for Person-Oriented Research, 6*(1). https://doi.org/10.17505/jpor.2020.22042

Wichers, M., Wigman, J. T. W., & Myin-Germeys, I. (2015). Micro-level affect dynamics in psychopathology viewed from complex dynamical system theory. *Emotion Review: Journal of the International Society for Research on Emotion, 7*(4), 362–367.

Williams-Kerver, G. A., Wonderlich, S. A., Crosby, R. D., Cao, L., Smith, K. E., Engel, S. G., Crow, S. J., Peterson, C. B., Mitchell, J. E., & Le Grange, D. (2020). Differences in affective dynamics among eating-disorder diagnostic groups. *Clinical Psychological Science, 8*(5), 857–871. https://doi.org/10.1177/2167702620917196

Witherington, D. C., & Crichton, J. A. (2007). Frameworks for understanding emotions and their development: Functionalist and dynamic systems approaches. *Emotion, 7*, 628–637.

Xu, W., Liu, X.-H., & Liu, R. (2015). Effect of mindfulness training improving emotional inertia: Moderation role of mindfulness trait. *Chinese Journal of Clinical Psychology, 23*(6), 1129–1132.

Yaroslavsky, I., Bylsma, L. M., Rottenberg, J., & Kovacs, M. (2013). Combinations of resting RSA and RSA reactivity impact maladaptive mood repair and depression symptoms. *Biological Psychology, 94*(2), 272–281.

Zheng, Y., & Asbury, K. (2019). Genetic and environmental influences on adolescent emotional inertia in daily life. *Journal of Youth and Adolescence, 48*(9), 1849–1860. https://doi.org/10.1007/s10964-019-01075-2

Chapter 5
A Close Look at the Role of Time in Affect Dynamics Research

Gal Lazarus, Jiyoung Song, Christopher M. Crawford, and Aaron J. Fisher

Abstract Affective experiences and related cognitive and motivational processes unfold within individuals over time. Vital information is inherently embedded in the time scale, shape, and context of affective processes' temporal dynamics. Thus, time itself may serve as a useful proxy for various underlying causal processes that researchers can identify and model. Considering the role(s) of time in theoretical conceptualizations and including time-derived variables in statistical models is likely to significantly improve the understanding of affect dynamics and their place among other dynamic processes. In this chapter, we delineate three sets of factors to be addressed in the study of affect-related temporal dynamics: The first set concerns the time scale in which the target system's core processes unfold. The second set concerns the shape of temporal (co)variation within the target system—that is, the trends, cycles, and discrete phenomena involved. The third set concerns the sources of within-individual variation in the target system across time and context. Although many of these themes have already been spelled out in the affect dynamics literature, their incorporation into research remains limited. Facing recent concerns regarding the robustness of affect dynamics findings and renewed interest in psychological theory development, thorough consideration of temporal dynamics becomes crucial.

Keywords Affect dynamics · Time scales · Cycles · Idiographic methods

5.1 Introduction

Psycho-behavioral phenomena unfold within individuals over time (e.g., Fisher et al., 2018; Hamaker & Wichers, 2017). Accordingly, a basic (implicit or explicit) tenet in the theoretical definitions of many psychological constructs and processes

---

G. Lazarus (✉) · J. Song · C. M. Crawford · A. J. Fisher
Department of Psychology, University of California, Berkeley, Berkeley, CA, USA
e-mail: jiyoungsong@berkeley.edu; cmcrawford@berkeley.edu; afisher@berkeley.edu

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_5

is their presence and development within individuals and along time (e.g., Fisher, 2015; Wright & Zimmermann, 2019). Only in recent years, various strands of research have adapted their designs to correspond to this fundamental truth by collecting intensive longitudinal data and modeling them while considering (to various degrees) the role of time (for a recent review, see Trull & Ebner-Priemer, 2020). Such approaches offer the opportunity to examine psychological processes as they unfold in individuals' daily lives and assess their *dynamics*.

Dynamic indices quantify the time-dependent (co)variation present within repeated measurements of one or more variables. Ideally, specific indices would function as operationalizations of well-defined affect-related processes. In the present chapter, we first point out that the time-dependency of affect dynamics indices creates ambiguity in their interpretation that is often unrecognized. Then, we argue that to address this ambiguity, researchers should attend to the distinct time-related effects present in their data by considering and modeling the rich information the passage of time represents. Subsequently, we specify three sets of time-related factors that can guide such consideration—the time scale in which the core processes of the target system unfold, the shape of temporal (co)variation within the target system (e.g., trends, cycles), and the sources of within-individual variation in the target system across time or context. We conclude by offering an integrated perspective of the different sets and emphasizing some practical recommendations vis-à-vis the field's current state.

5.2 The Role(s) of Time in Affect Dynamics

One field that has benefited significantly from the recent methodological advances in data collection and modeling is affective science, in which the study of affect dynamics has flourished (e.g., Kuppens, 2015; Kuppens et al., 2010a, b). Various indices quantifying the patterns with which emotions or moods (co)vary across time have been suggested (e.g., mean square successive differences [MSSD], autoregression) and found to be associated with indices of psychological well-being (e.g., Houben et al., 2015), personality (Erbas et al., 2014), and psychopathology (e.g., Trull et al., 2015). Despite the growing interest in affect dynamics and the accumulating findings regarding their correlates, recent work utilizing large and diverse samples has shown that specific affect dynamics indices may have little incremental validity beyond affect mean and variability in predicting indices of psychological well-being (e.g., Dejonckheere et al., 2019), psychopathology (Bos et al., 2019), and personality (Wendt et al., 2020).

How can findings demonstrating poor incremental validity of affect dynamics indices be reconciled with the strong intuition and sound reasoning that the patterns with which individuals' affect change over time hold unique and important information regarding their psychological characteristics? In this chapter, we contend that some of the observed limitations in current affect dynamics research stem from theoretical ambiguity regarding the underlying data generating processes that give rise to specific affect dynamics. It is often the case that the processes involved in the dynamics themselves, including the identity of their components, the relations between them, their putative effects, and the ways all these unfold in time, are only vaguely defined. Theoretical statements with greater specificity (e.g., regarding the emotions involved), quantifiable features, (e.g., the size and the shape of expected associations, e.g., Haslbeck et al., 2019), delineation of circumstances in which effects are expected (Fried, 2020; Yarkoni, 2020), and an emphasis on causal inference may each contribute to the generation of stronger affect dynamics theory. Importantly, as we endeavor to uncover *causal* explanations for individual behavior, delineating underlying—likely neurobiologically-derived—sources of variation from more reflexive, cognitive-affective responses to external stimuli will help to refine and sharpen our theoretical argumentation.

The MSSD, for example, summarizes the average within-person (squared) differences between consecutive observations. As applied to the dynamic unfolding of negative affect (NA) in daily life, higher levels of these differences are thought to be generated by emotion regulation difficulties. Indeed, MSSD in NA has been found to be associated with indices of psychological maladjustment (for a meta-analysis, see Houben et al., 2015) and is often referred to as emotional or affective instability (Trull et al., 2015). However, at least some of these within-person NA successive differences are likely generated by flexible adjustments to environmental demands and adaptive internal processes.

Identifying the actual data generating processes underlying specific affect dynamics indices is likely to require both theoretical deliberation and methodological innovation. In the above example, theory-driven contextual factors (e.g., some situational features) that may be relevant to the specific population may be introduced to the measurement scheme. Whereas the temptation to measure many contextual factors is understandable, researchers are limited in their ability to expand the breadth of data collected in each survey to avoid overburdening participants. This constraint is especially pressing in the high-measurement-frequency designs that are often employed in affect dynamic studies. Hence, thoughtful consideration of the most informative and temporally pressing contextual features is essential for maximizing the predictive validity of ambulatory data sources.

The temporal unfolding of the data contains rich and essential information, waiting to be examined (e.g., Jebb et al., 2015; van de Maat et al., 2020)—and potentially mined for causal explanations. For instance, although some affective fluctuations cannot be predicted by any measured variable and may only be categorized as unexplained instability, other fluctuations may follow a fixed time-related pattern (e.g., diurnal), allowing researchers to generate specific time-dependent hypotheses about underlying causal processes (such as diurnal variation in cortisol). Thus, rather than reflecting volatility in underlying processes, some sources of variability may represent stable fluctuations that follow consistent daily (approximately 24-h), ultradian (less than 24-h), or infradian (more than 24-h) patterns. One study, which examined fluctuations in daily anxiety, proposed that diurnal variation in distress was likely the result of unresponsiveness to environmental contingencies, a pattern which improved during successful cognitive-behavioral therapy (e.g., Fisher

& Newman, 2016). Though largely semantic, one takeaway from these findings is that the variability in these data seemed to reflect emotional rigidity, rather than instability.

In general, greater consideration of the role(s) played by time might clarify the underlying mechanisms that affect dynamic indices attempt to capture. In analyses of human emotion and behavior, time is likely to be an ever-present hidden third variable. Because all processes—whether causal, reflexive, or epiphenomenal—unfold over time, vital information will be inherently embedded in the scale and structure of the temporal dynamics of those processes. Thus, time itself may be a useful proxy for uncovering and understanding underlying causal processes that are yet to be identified or otherwise unmeasured. It follows that including time in our theoretical conceptualizations may shed light on the understanding of dynamic processes and including it in our statistical models is likely to significantly alter the findings and their interpretation. For instance, failure to account for linear trends in longitudinal data can artificially inflate correlations between two longitudinally measured variables (e.g., Falkenström et al., 2017).

Thorough consideration of the role(s) of time necessitates careful estimation of the particular affect-related processes that comprise the target phenomena for a particular population under particular conditions. Specifically, relying on relevant existing theories and prior findings, researchers should consider three sets of determinants. The first set concerns the time scale. How quickly does a given process occur? How should measurement paradigms and analyses be calibrated to accommodate and accurately reflect the temporal scaling? These decisions are paramount for determining the magnitude of (co)variation at varying intervals between consecutive measurements within a target system (e.g., Adolf et al., 2021; Dormann & Griffin, 2015), informing interpretations of vital phenomena such as autocorrelations and cross-lagged predictions. The second set relates to the *shape* of temporal (co)variation within the target system—that is, the trends, cycles, and discrete phenomena (i.e., dichotomous, present or absent events) that make up the patterns of variation in the data. These features can be thought of as the system's temporal *structure*, the building blocks of (co)variation at various time scales and measurement intervals. Finally, the third set concerns sources of within-individual variation in affect dynamics (e.g., Bringmann et al., 2018; Koval & Kuppens, 2012) across time or context that may be relevant for the target system. Moreover, these within-individual processes are likely to result in between-individual variation (i.e., individual differences) in affect dynamics. Thus, care should be taken to assess and possibly categorize within-individual heterogeneity in affect dynamics.

Importantly, such theoretical clarity, in our view, may benefit both measurement and modeling practices in the study of affect dynamics. Measurement practices, for example, can be improved by considering the appropriate time scales and frequency (e.g., lag length, signal/event trigger), questionnaire instructions (e.g., adjusting the frame of reference of the affect item), and/or contextual variables that most accurately represent underlying data generating process. Modeling practices can be improved by selecting appropriate statistical frameworks (e.g., regression, network, non-linear models), including relevant temporal variables representing trends (e.g., linear) or cycles (e.g., diurnal), and/or estimating time-varying effects. In the following sections, we expand the discussion of the three sets of determinants as applied to theory, measurement, and modeling.

5.3 Time-Related Considerations in Affect Dynamics Research

5.3.1 Choosing the Appropriate Time Scale

Numerous leading affect dynamics researchers have recognized the importance of the time scale at which affect is being measured and modeled (e.g., Butler, 2015; Hollenstein, 2015; Kuppens, 2015), and similar recognitions have been made for other psychological processes studied using intensive longitudinal methods (e.g., Boker et al., 2009; Hamaker & Wichers, 2017; Neubauer & Schmiedek, 2020). Indeed, assessing affect hourly, as opposed to daily, for example, would not only produce different profiles of change, but also most likely reflect different affective processes altogether (Koval et al., 2013).

Surprisingly, extensive meta-analytic work conducted thus far indicates that the time scale at which affect dynamics are assessed does not appear to significantly moderate observed relationships with psychological well-being indices (Houben et al., 2015). As the authors noted, however, the reviewed literature has mostly consisted of studies measuring changes in affect across hours or days, as opposed to minutes or seconds. We also must ask ourselves whether the same affect dynamic, measured at different time scales, represents the same underlying construct or data generating process. For instance, much is made of the contrast between emotion and mood, where the former is thought to operate on a faster, contextualized time scale, and the latter is thought to be a slower-moving, possibly characterological phenomenon. Thus, while similarity in correlations between affect dynamics and other variables of interest across multiple time scales may indicate some degree of consistency, such correlations cannot comment on the nature of the relationship between the affect dynamic and the other variable. Assessing the magnitude of the similarity between specific affect dynamic indices derived from different time scales may constitute a preliminary step before assessing causal relationships with other constructs.

Clarifying the role of different time scales in the study of affect dynamics (not only in relation to other constructs but also within the affective dynamic indices themselves) requires empirical investigation and careful theoretical reasoning. In an important contribution, Ebner-Priemer and Sawitzki (2007) measured subjective distress every 15 min for 24 h and then compared the observed time series to those randomly shuffled within each person (i.e., without the sequentially-dependent structure) across different time scales. They found that only time series based on time scales equal to or shorter than one hour could be distinguished from randomly shuffled ones. This pattern was present both for individuals with borderline personality disorder (BPD) and healthy controls. The authors concluded that distress dynamics derived from time series with intervals longer than one hour are likely to altogether ignore the target system's temporal structure.

The common use of longer than one-hour time scales in affect dynamics research may shed light on some recent findings. First, the lack of incremental predictive validity of the *time-dependent* instability indices (Bos et al., 2019; Dejonckheere et al., 2019; Wendt et al., 2020) over the *time-independent* variability indices may be explained if the time scale used cannot reflect true temporal unfolding of affect. Second, the presence of specificity of affective variability in individuals with BPD, but not of affective instability (e.g., Houben et al., 2020; Mneimne et al., 2018; Santangelo et al., 2016), may similarly reflect the limited ability of the design to capture valid time-dependency.

By and large, assessing target processes at time scales larger than those at which processes unfold may result in misleading or inaccurate inferences. In the example study below, we demonstrate the impact of varying time scales on commonly used operationalizations of affective instability and inertia (i.e., autoregression).

5.3.1.1 Example Study 1

Data for this example study come from Fisher et al. (2017). Participants ($N = 80$) were a mixture of individuals with primary diagnoses of generalized anxiety disorder ($n = 23$), major depressive disorder ($n = 11$), or both ($n = 11$), and healthy controls ($n = 35$). Those with diagnoses were enrolled in an open trial of a personalized cognitive-behavioral intervention for mood and anxiety disorders. Before engaging in any intervention, all 80 individuals completed 30 days of self-reported EMA surveys four times per day. In each survey, participants rated their experience of each item over the preceding hours using a 0-100 visual analog slider with the anchors "not at all" and "as much as possible" for the 0 and 100 positions, respectively. In the present study, positive affect (PA) was assessed with a single-item measure (Song et al., 2021), and NA was calculated by averaging the angry, irritable, guilty, afraid, down, worried, and hopeless items at each time point.

In the present investigation, we examined seven different time scales: all four surveys (4-h intervals), first and third surveys of each day (8-h interval), second and fourth surveys of each day (8-h interval), and once a day for each of the four surveys (e.g., first survey of each day, second survey of each day, etc.; 24-h interval). We calculated affect dynamics intra-daily for the 4-h and 8-h time scales and inter-daily for the 24-h time scales. Of the affect dynamics, we chose to examine instability (the magnitude of moment-to-moment emotional changes) and inertia (the magnitude of moment-to-moment emotional carry-over) because they are time dependent and thus most likely to vary across time scales.

Table 5.1 presents the correlations between the instability indices, and Table 5.2 presents the correlations between the inertia indices. Across the seven time scales, instability (mean r: 0.77; range: 0.64–0.91) was generally more well correlated than inertia (mean r: 0.31; range: −0.03–0.65) for both PA and NA. Still, instability was nevertheless dependent on the time scale in which it was measured, with

Table 5.1 Correlations of affect instability indices across seven time scales

Time scale	1	2	3	4	5	6	7
1. Four times a day		.83	.86	.77	.68	.76	.76
2. First and third surveys each day	.91		.78	.76	.73	.68	.80
3. Second and fourth surveys each day	.90	.80		.76	.77	.72	.79
4. First survey each day	.80	.83	.74		.68	.64	.77
5. Second survey each day	.81	.79	.82	.74		.72	.70
6. Third survey each day	.83	.87	.78	.69	.75		.71
7. Fourth survey each day	.82	.70	.83	.76	.73	.69	

Note. Positive affect correlations are below the diagonal, and negative affect correlations are above the diagonal

Table 5.2 Correlations of affect inertia indices across seven time scales

Time scale	1	2	3	4	5	6	7
1. Four times a day		.53	.54	.34	.43	.36	.34
2. First and third surveys each day	.57		.36	.32	.31	.17	.22
3. Second and fourth surveys each day	.65	.32		.23	.42	.31	.35
4. First survey each day	.17	.35	.20		.37	.39	.31
5. Second survey each day	.26	.21	.20	−.03		.26	.18
6. Third survey each day	.38	.34	.34	.07	.33		.36
7. Fourth survey each day	.37	.24	.29	.17	.15	.30	

Note. Positive affect correlations are below the diagonal, and negative affect correlations are above the diagonal

overlapping variance ranging from 41 to 83%, leaving anywhere from 17 to 59% of the variance unexplained. Thus, changes in emotional experience that unfold over a span of an hour versus 4, or 24 h are not likely to reflect the same psychological phenomena, and future studies should look to uncover the sources of unexplained variance in different constructs across differing time scales.

The inconsistency in inertia values across time scales was salient—on average, there was less than 10% of shared variance between two inertia values derived from two different time scales. This finding may indicate that the autocorrelation metric may reflect different psychological processes as a function of the time scale from which it derived (or that it fails to capture any single process reliably). The sensitivity of the inertia index to the lag-length may explain some of the mixed findings regarding inertia's associations with psychopathology indices, and specifically with depression.

Indeed, using second-by-second time-series data collected in the lab, Kuppens et al. (2010a, b) found that depressed participants exhibited a higher level of negative affect inertia than nondepressed participants. Conversely, Thompson et al. (2012) and Bos et al. (2019) used EMA consisting of 8 and 3 surveys per day, respectively, and found no significant association between inertia and depression indices. Contrasting these findings further, Brose et al. (2015) did find a significant association between inertia derived from daily affect reports and depression symptoms, yet their sample eschewed clinical participants. Supporting the notion that time scale matters, Koval et al. (2013) showed in a single sample that higher inertia of NA in the lab (based on less than a minute intervals), but not in daily life (based on hours intervals), is predictive of depressive symptoms.

There might exist a threshold at which substantive similarity in psychological process is preserved across time scales (e.g., Houben et al., 2015). Identifying such a threshold is an important scientific endeavor, and until it is established researchers may be wise to either oversample—as Ebner-Priemer and Sawitzki (2007) did to identify the time scale at which the target psychological process operates—or choose a time scale based on a sound, concrete theory or empirical findings that offer temporal information about the phenomenon of interest. An important source of such information are studies assessing emotion duration (e.g., Kalokerinos et al., 2017). One such study has shown that 80% of reported emotions return to baseline in less than an hour (Verduyn et al., 2009).

5.3.1.2 Special Consideration for Lag Lengths

The lag lengths used in the analyses of (and indices calculated from) time-series data can differ, that is, be longer, than the measurement interval used for data collection. Indeed, different processes measured in an EMA study may unfold in different time scales and require adjusting the lag length accordingly (see Jacobson et al. [2019], who recently developed a tool to automate the process of detecting optimal lag lengths). Different lag lengths are likely to influence the magnitude (and shape) of lagged associations and time-dependent affect dynamics (e.g., Adolf et al., 2021; Dormann & Griffin, 2015).

Only a few affect dynamics studies to date, however, have empirically examined the role of lag length, and most researchers default to a lag-1 structure. Such practices may be problematic not only because a lag-1 structure may represent different time intervals across different studies but also because it disregards individual differences in psychological and affective trajectories (Boker et al., 2009). To demonstrate the presence of such individual differences, in our second example study, we examined which lag length produced the maximal inertia values for each individual in our PA and NA data.

5.3.1.3 Example Study 2

The data employed for Example Study 2 were again the 80 participants from Fisher et al. (2017). Here we examined seven different lag lengths: 4 h, 8 h, 12 h, and 24 h. For the daily (i.e., 24-h interval) lag length, we once again separated the four daily surveys to create four separate lag conditions. For each of the 80 participants, we computed PA and NA inertia values derived from the seven different lag lengths and determined which of them resulted in the maximum autocorrelation. Figures 5.1 and 5.2 present the distribution of the optimal lag lengths (i.e., the lag with the highest autocorrelation) for PA and NA, respectively.

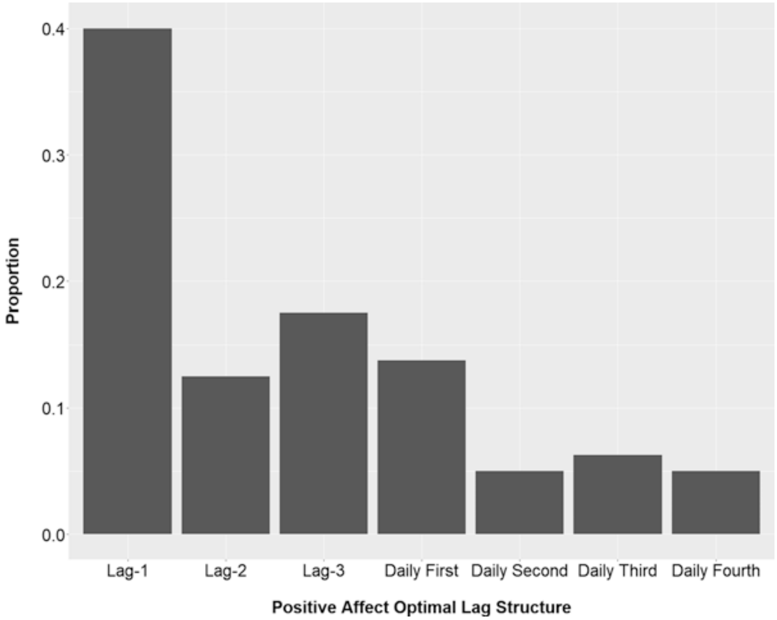


Fig. 5.1 Optimal Lag Structure for Positive Affect

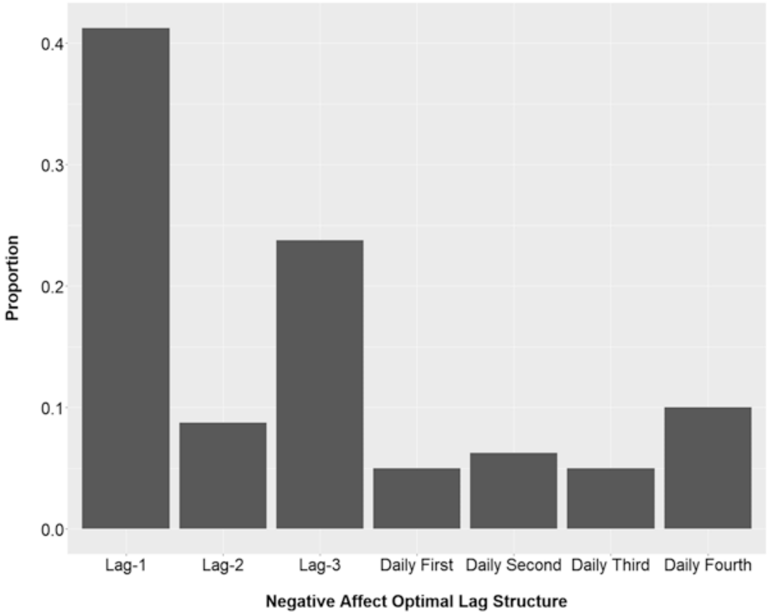


Fig. 5.2 Optimal Lag Structure for Negative Affect

As can be seen in Figs. 5.1 and 5.2, for both PA and NA, about 40% of the participants' highest autocorrelation resided within the shortest lag length available in our study (i.e., 4 h). This was expected, as the shortest time interval offers the least number of opportunities for participants to have experiences that may shift their affective states. However, the optimal lag length for the remaining 60% of the participants ranged from 8 to 24 h. The observed heterogeneity in optimal lag length also included time of day. That is, for the participants whose optimal time lag was 24 h, there was heterogeneity in which of the four daily surveys produced the largest inertia value (morning, midday, evening or nighttime).

For affect dynamics to adequately capture a psychological process of interest, we suggest careful, theoretically grounded consideration of the time intervals at which such processes operate. Conversely, identifying optimal lag lengths for each individual might require more data-driven approaches to adequately describe the temporal pattern unique to each person. Thus, effective utilization of affect dynamics as tools to understand psychological processes and mechanisms requires both sound theory and data analytic strategies.

5.3.2 Considering Linear and/or Cyclical Time Effects

The dynamic change of repeatedly measured variables is subject to the influence of various factors associated with the passage of time. They often render the time series of these variables non-stationary, that is, one with distributional characteristics (e.g., mean, variance, autocorrelations) that change across time and/or context (e.g., Molenaar & Campbell, 2009). The manifestations of these factors can be divided into two general groups: trends and cycles. Trends reflect relatively macroscopic shifts in a variable's mean over the measurement period. Conversely, cycles reflect more granular temporal processes that rise and fall in likelihood at 12-h, 24-h, weekly, monthly, and/or seasonal frequencies. Researchers can model these patterns and assess their impact by creating variables that reflect the wide range of temporal dynamics, including trends, cycles, and regular intervals (e.g., time of day). In this section, we discuss the relevance of different types of trends and cycles for affect dynamics research. Specifically, we posit that ignoring such patterns may result in misinterpreting the meaning (i.e., the underlying data generating processes) of affect dynamics indices.

Trends are familiar among researchers employing intensive longitudinal methods. The most commonly examined trend is linear, capturing stable directional changes in a time series. There are occasions when a time series exhibits higher-degree polynomial trends indicating that its values tend to rise or fall at a rate that is not constant. For example, a quadratic trend suggests that the rate of change decreases or increases over the measured time period and may also account for changes in the slope's direction (e.g., initial increase followed by a decrease). Higher-level polynomials (e.g., cubic) allow for more complex patterns of change (Jebb et al., 2015).

EMA-based affect dynamics studies typically involve a week to month-long time series, which are likely to contain time trends. Such trends may be caused by external events that are emotionally significant to participants. For example, an impending exam—a common event among undergraduate samples used in affect dynamics research—will likely induce an increase in anxiety levels until the test, which may then gradually dissipate following the test. Depending on the specific place the exam takes along the time series, different trends may emerge. Notably, also lab-based affect time series may contain trends which are often caused by situational demands (e.g., high arousal at the beginning of a videotaped interaction that wears off with the passage of time).

The presence of time trends may increase correlation-based intrapersonal affect dynamics indices such as inertia, possibly confounding two data generating processes: the extent to which an emotion is resistant to a change (i.e., "true" inertia), and the increasing or decreasing effect of an external event. Similarly, in the case of interpersonal affect dynamics, synchrony measures will be strongly affected when both persons' data series share a similar time trend (e.g., due to shared event or context). Here, too, an association between the two time series will not be solely the product of affective processes often considered to underlie such associations (e.g., transmission or similar affective reactions to immediate contextual factors).

Whereas linear time trends are often considered in affect dynamics studies (e.g., Butler, 2011; Trull et al., 2015), cyclical effects are typically ignored (despite high quality work stressing their importance, c.f. Larsen, 1987; Hamaker & Wichers, 2017; Ram et al., 2005; van de Maat et al., 2020). These effects may stem from various sources and manifest across a wide range of time scales. Diurnal patterns have received the most attention, and research examining the temporal patterning of affect in daily life has observed robust daily periodicities. PA, for example, has been found to follow a diurnal pattern, increasing from morning to early afternoon and falling in the evening (Golder & Macy, 2011; Clark et al., 1989). Conversely, NA was found to decrease during the morning hours and increase throughout the remainder of the day (Golder & Macy, 2011). Furthermore, work assessing relations between affect dynamics and circadian rhythms has demonstrated that a significant amount of within-day variance in PA can be explained by a 24-h sinusoid, with greater effect sizes observed in conditions characterized by constant and controlled sleep cycles (Murray et al., 2009). These diurnal patterns may be driven by both exogenous contextual factors (e.g., Beal & Ghandour, 2011) and endogenous psychophysiological ones (e.g., Adam et al., 2017). Notably, the ability to identify cycles depends on the duration of the data collection period and should be a part of the factors considered in the study design.

Importantly, cyclic affective patterns are not limited to the daily time scale. Indeed, there is evidence for weekly affective cycles (e.g., Beal & Ghandour, 2011; Liu & West, 2016), which may stem from factors such as the structure of the work week (e.g., with greater stress during the weekdays). Additionally, monthly affective patterns have been observed and were found to be associated with menstrual cycles (Farage et al., 2008; though see Hengartner et al., 2017) and lunar tidal cycles (Wehr, 2018). This corpus of work suggests that despite the conceptualization of affect as being constantly modulated by relatively stochastic internal and external events, stable patterns of variation are common.

Figure 5.3 provides a visual illustration of simulated time-related effects on a single participant's time series data. As can be seen in the figure, despite their strength (vs. the random deviations from the mean), these effects are not easily

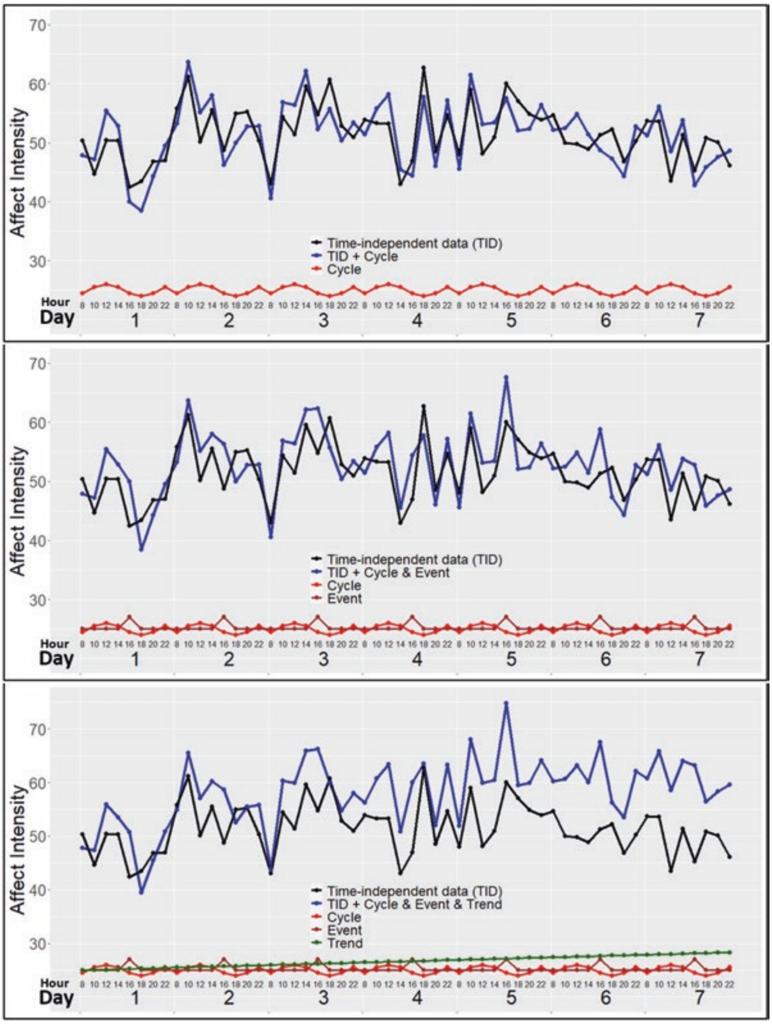


Fig. 5.3 A visual illustration of time-related effects on a single participant's time series data. The original time series (black) was derived from random normally distributed data [Mean = 50, Standard deviation (SD) = 5] and is time-independent. Each of the panels shows the original time series, an additional time series modified by time-related effects (cycle, event, and trend), and a representation of the modifiers (red, brown, and green). The upper panel's time series was modified by a 12 h cycle with an effect size equal to one SD. The central panel's time series was modified by the same cyclic effect and a single daily event effect (at 16:00 each day) with an effect size equal to two SDs. The lower panel's time series was modified by the same cyclic and event-related effects, as well as by a linear trend with an effect size equal to approximately two SDs

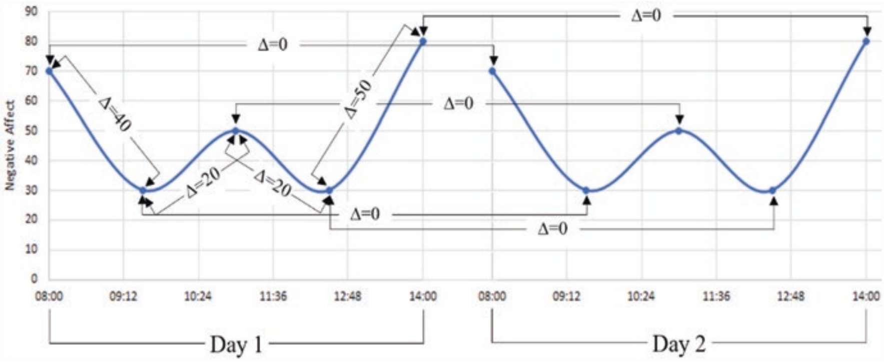


Fig. 5.4 Demonstration of negative affect levels fluctuating along the first part of two consecutive days and the corresponding absolute differences in negative affect at lags of 1 observation (lower Δ's) and 5 observations (uppermost Δ)

recognizable by the naked eye. This visualization demonstrates the importance of making the modeling of time-related effects an integral part of any affect dynamics exploration.

Cyclical patterns may play a similar confounding role to the trends described above when examining correlation-based indices. Importantly, they may have an additional substantive impact on understanding differences-based indices (e.g., MSSD) that are used as operationalizations for affective instability. These indices ignore the broader temporal structure of the construct that they purport to describe. Specifically, the MSSD—representing the average magnitude in observation-to-observation fluctuations over time—does not assess the degree to which variations in affect represent stable, repeating patterns.

Consider the following example: a high school student experiences an increase in NA while waiting in the cold for the bus. This NA quickly subsides, however, as the student reunites with their friends before class. Their NA levels continue to rise and fall over the course of the day as they engage with unpleasant (e.g., speaking in front of the class) and pleasant (e.g., eating lunch with friends) stimuli, and these fluctuations persist from day-to-day and week-to-week. A visual representation of these fluctuations in NA can be seen in Fig. 5.4. As operationalized by the MSSD, this time series would be characterized as unstable, but this quantification obscures the fact that these fluctuations are stable at the between-day level.

Research by Fisher and Newman (2016) has demonstrated the importance of considering such cyclical patterning in the context of a therapeutic intervention for individuals diagnosed with generalized anxiety disorder (GAD). The authors hypothesized that since for individuals with GAD, the feared outcomes in worry episodes may be invoked regardless of external context, they may become entrained to fixed patterns of anxiety on a day-to-day basis. Indeed, using spectral analysis (Scargle, 1982) and spectral power to determine the degree to which variation in daily anxiety symptoms was related to the presence of sinusoids in the data, Fisher and Newman found that the observed diurnal rigidity—the degree to which anxious distress was dictated by 24-h periodic patterns—decreased throughout the therapeutic intervention, and the degree to which rigidity was reduced was associated with reliable change post-treatment. Moreover, this reduction in periodicity predicted reliable change post-treatment even when controlling for change in MSSD (which did not significantly predict the treatment outcome). The implication of these findings is straightforward: when variability in a construct of interest over time is best characterized by stable, cyclical patterns (e.g., a sinusoid), the use of the MSSD as an operationalization of instability may provide misleading results.

This example illustrates a crucial point—the reason for modeling the effects of time is not necessarily only to statistically adjust for them (using methods such as detrending). In cases where the dynamics of interest do not form stationary fluctuations but a trend or a cycle, detrending will result in throwing out the baby with the bathwater (e.g., Wang & Maxwell, 2015). For instance, Butler and Randall (2013) describe interpersonal morphogenic processes (e.g., mutual arousal modulation towards optimal bounds), which are trend-driven interpersonal affect dynamics. Hence, researchers should consider the meaning of trends and cycles on a case-by-case basis.

5.3.3 Modeling Within-Individual Variability in Affect Dynamics

As noted above, affect and affect-related processes are often non-stationary. Hence, affect dynamics themselves can, and often do, vary not only between but also within individuals (e.g., Albers & Bringmann, 2020; Bringmann et al., 2017). For example, both affect polarity (Dejonckheere et al., 2021) and affect differentiation (Erbas et al., 2018) were found to change as a function of stress. Importantly, on some occasions, such changes may be a central outcome variable. For example, Van der Gucht et al. (2019) showed that affect differentiation increased following a mindfulness-based intervention.

Exploring changes in affect dynamics is possible with or without pre-existing expectation or knowledge regarding the nature of change and/or its timing. In cases where the timing of changes is expected, such as following an intervention (Van der Gucht et al., 2019), separate affect dynamics indices can be calculated for different sections of the individual's data. Additionally, contextual variability in an individuals' time-series (e.g., daily stress) can be tested as a predictor of local affect dynamics indices (e.g., Dejonckheere et al., 2021; Erbas et al., 2018). In cases where the timing of changes or their predictors are unknown, data-driven statistical methods can be used to detect both gradual (e.g., Bringmann et al., 2017, 2018) and abrupt (e.g., Albers & Bringmann, 2020; Cabrieto et al., 2018) changes in the time series.

The presence of within-individual variation in affect dynamics brings about interesting research directions. First, modeling affect dynamics indices as within-individual predictors or outcomes corresponds more closely to the psychological theories that conceptualize psychological processes as unfolding within individuals over time (c.f. Molenaar & Campbell, 2009). This approach can add an explanatory process-focus layer to a field that has been largely focused on descriptive individual differences. For example, lower differentiation between negative emotions is thought to lead to greater psychological distress (Pascual-Leone & Greenberg, 2007). Considering emotion differentiation (ED) as a trait or stable ability and measuring its association with distress indices is informative and useful but tells us very little about the way ED works in the within-individual level (Fisher et al., 2018). Examining the effects of within-individual ED (Erbas et al., 2021) allows for a better assessment of the dynamic processes involved and hence for a more direct theory testing and development (e.g., Haslbeck et al., 2019).

Relatedly, the recognition that affect dynamics themselves change across time as a function of contextual factors invites examining them under different conditions. In light of recent findings regarding the limited incremental predictive validity of affect dynamics, the field may likely benefit from identifying the exact conditions under which they may exert more robust effects (Dejonckheere et al., 2020; Lapate & Heller, 2020). Notably, when the focus is on specific conditions, researchers may want to trade the goal of obtaining a representative yet sparse assessment of the entire day for a focused and more frequent assessment in the time of interest. Furthermore, researchers can estimate dynamics that are derived from affect data collected in specific contexts in which affect plays a particularly central role (e.g., psychotherapy sessions—Galili-Weinstock et al., 2020; Lazarus et al., 2019). Altogether, a contextualized, systems-related perspective on affect dynamics places these metrics within their intended domain of dynamic, time-dependent emotional functions.

Lastly, the presence of within-individual variation in affect dynamics calls for employing an idiographic approach (e.g., Fisher et al., 2017; Molenaar & Campbell, 2009; Wright & Zimmermann, 2019) and invokes the question regarding the extent to which the associations between these dynamic indices and other constructs generalize from the between-individual level to the within-individuals level (i.e., the extent to which the associations are ergodic; Fisher et al., 2018; Molenaar, 2004). Importantly, the inferences drawn at one level may differ from an inference drawn at another level. For example, at the between-individual level, individuals who demonstrate greater fluctuations in affect are thought to have poorer regulation skills and lower psychological well-being (e.g., Houben et al., 2015). However, at the within-individual level, are greater periodic emotional fluctuations indicative of lower or less effective regulation? It is entirely possible that momentary increases in emotion fluctuation could represent spikes in negative affect followed by subsequent successful down-regulation—a sequence which could look like instability without appropriate contextualization. The answers to such questions are likely to be quite complex. We may expect a considerable variation in the magnitude (e.g., Fisher et al., 2018) and the shape of the intraindividual associations which may warrant within-person data analysis and render generalizations hard to attain.

Despite the major challenges posed by idiographic modeling of affect dynamics, it likely holds great promise. Clinicians have expressed interest in the potential of employing an idiographic approach in assessment and intervention planning (Fisher, 2015; Piccirillo & Rodebaugh, 2019; Wright & Woods, 2020). Affect and affect-related constructs play a central role in such clinical efforts, though these efforts often employ novel modeling techniques at the expense of the traditional affect dynamics indices (Fisher et al., 2019; Fisher & Bosley, 2020). Indeed, the shift from assessing between-individual differences in a set of fixed indices to identifying person-specific clinically significant affective patterns calls for the creation of personalized indices that comprise personalized arrangements of items.

5.4 Concluding Thoughts

Time is the medium through which affective experiences and related processes unfold. It encapsulates the effects of myriad unmeasured variables. In this chapter, we illustrated how a thoughtful consideration of time-related patterns could enrich the conceptualization, measurement, and modeling of affect dynamics. To do so, we delineated three sets of determinants to be addressed: the first pertains to the temporal scaling of the studied phenomena, that is, the time scales suitable to capture and model the phenomena; the second pertains to the *structure*, the shapes of the (co) variation in the data source. These relate to the trends, cycles, autoregression, and cross-predictions embedded in the data. The third pertains to the within-individual *variation* across time in the studied phenomena. We simply expect people to differ in any and all ways, including those pertaining to the temporal scale and structure of their affective experience.

Notably, these different sets should be considered in tandem. For example, different trends and cycles may be more prominent at different time scales. Furthermore, there is likely to be not only between-individual variability in the optimal time lag (as we show in Example Study 2) but also within-individual variability. Similarly, the strength of specific trends or cycles is also likely to vary within individuals. For example, affective diurnal cycles were shown to change as a function of psychological interventions (Fisher & Newman, 2016).

Including a thorough evaluation of the role of time in our array of considerations when studying dynamic processes may seem to bring with it an unwieldy range of measurement and modeling options. Ideally, decisions in these matters would be guided by fine-grained theories relevant to the phenomena of interest. Unfortunately, current psychological theories are often not specific or accurate enough to provide such guidance. Typically, such theories remain silent about the magnitude, shape, and direction of associations, or the time scales and contextual conditions under which they are likely to appear (Fried, 2020).

In a series of recently published papers, leading theorists and methodologists have identified a “theory crisis” in psychological science (e.g., Borsboom et al., 2021; Eronen & Bringmann, 2021; Fried, 2020). These authors contend that the field suffers from a lack of proper theory construction and testing procedures and that most psychological theories are weak in their accuracy and testability. We believe that a rigorous exploration of time-related processes of the sort we describe here can contribute to constructing stronger and more cumulative theories in psychological science.

Notably, an essential part of constructing a stronger affect dynamics theory is contextualizing them in a manner that allows drawing causal inferences. We must ask whether affect dynamics are themselves derived from underlying causal systems, or whether they are reflective of adaptive or maladaptive responses to environmental demands. For instance, current theory regarding the MSSD statistic posits that the absolute value of changes in affect from moment to moment represents the stability versus volatility in the selected affect measure. What remains to be understood is whether this volatility is reflective of lability in neurobiological emotion-generating processes, whether it reflects anxiogenic, depressogenic, or generally dysphoric schemata that amplify innocuous or ambiguous stimuli, or whether it reflects relatively adaptive responses to shifting environmental demands. Delineating these influences moves the MSSD beyond descriptive or statistical utility into a potentially causal role.

To increase our chances of constructing strong affect dynamics theories that involve causal explanations and accurate prediction, we may need to revise some of our methods. Though this chapter did not focus on describing specific methods, it does have some broad methodological implications. First and foremost, modeling trends and cycles in affect dynamics research is crucial for accurate interpretation of their meaning. Importantly, adjusting for such trends or cycles (for example, by using detrending) should not be done automatically since in some cases their presence is at the core of the phenomena of interest (e.g., Butler & Randall, 2013; Fisher & Newman, 2016). Additionally, the value in considering cycles is not limited to covariance-based dynamic indices (e.g., inertia, synchrony) but extends to difference-based indices (e.g., MSSD).

Second, adjusting the measurement frequency to the putative data generating processes of the target system may improve researchers' ability to accurately model them (e.g., Ebner-Priemer et al., 2007; Haslbeck et al., 2019). In the case of affect dynamics, that would usually mean using relatively high-frequency measurements (e.g., Verduyn et al., 2009). Recent findings support the feasibility of such designs as they indicate that increased sampling frequency is not tied with greater participant burden (but surveys' length does—Eisele et al., 2020). Third, measuring contextual variables is essential to improve our understanding of how and why affect changes across time, and particularly to make possible the examination of within-individual variation in affect dynamics.

Many of the themes described in this chapter have been pointed out before. The importance of time scale (e.g., Dormann & Griffin, 2015; Ebner-Priemer et al., 2007), linear or cyclical effects (Hamaker & Wichers, 2017; van de Maat et al., 2020), and within-individual variation (Dejonckheere et al., 2021; Erbas et al., 2018) has been acknowledged. To date, however, their incorporation into actual research efforts, whether in theory or study design, has remained rather limited. The current timing provides a unique opportunity for change—recent indications regarding the limited incremental predictive validity of affect dynamics indices (Bos et al., 2019; Dejonckheere et al., 2019; Wendt et al., 2020) and the growing attention to psychological theory development (e.g., Borsboom et al., 2021; Eronen & Bringmann, 2021; Fried, 2020), may be seen as an invitation to finally taking temporal dynamics seriously.

References

Adam, E. K., Quinn, M. E., Tavernier, R., McQuillan, M. T., Dahlke, K. A., & Gilbert, K. E. (2017). Diurnal cortisol slopes and mental and physical health outcomes: A systematic review and meta-analysis. *Psychoneuroendocrinology, 83*, 25–41. https://doi.org/10.1016/j.psyneuen.2017.05.018

Adolf, J. K., Loossens, T., Tuerlinckx, F., & Ceulemans, E. (2021). Optimal sampling rates for reliable continuous-time first-order autoregressive and vector autoregressive modeling. *Psychological Methods.*

Albers, C. J., & Bringmann, L. F. (2020). Inspecting gradual and abrupt changes in emotion dynamics with the time-varying change point autoregressive model. *European Journal of Psychological Assessment.* https://doi.org/10.1027/1015-5759/a000589

Beal, D. J., & Ghandour, L. (2011). Stability, change, and the stability of change in daily workplace affect. *Journal of Organizational Behavior, 32*, 526–546. https://doi.org/10.1002/job.713

Boker, S. M., Molenaar, P., & Nesselroade, J. R. (2009). Issues in intraindividual variability: Individual differences in equilibria and dynamics over multiple time scales. *Psychology and Aging, 24*, 858–862. https://doi.org/10.1037/a0017912

Borsboom, D., van der Maas, H. L., Dalege, J., Kievit, R. A., & Haig, B. D. (2021). Theory construction methodology: A practical framework for building theories in psychology. *Perspectives on Psychological Science*. https://doi.org/10.1177/1745691620969647

Bos, E. H., de Jonge, P., & Cox, R. F. (2019). Affective variability in depression: Revisiting the inertia–instability paradox. *British Journal of Psychology, 110*, 814–827. https://doi.org/10.1111/bjop.12372

Bringmann, L. F., Ferrer, E., Hamaker, E. L., Borsboom, D., & Tuerlinckx, F. (2018). Modeling nonstationary emotion dynamics in dyads using a time-varying vector-autoregressive model. *Multivariate Behavioral Research, 53*, 293–314. https://doi.org/10.1080/00273171.2018.1439722

Bringmann, L. F., Hamaker, E. L., Vigo, D. E., Aubert, A., Borsboom, D., & Tuerlinckx, F. (2017). Changing dynamics: Time-varying autoregressive models using generalized additive modeling. *Psychological Methods, 22*, 409–425. https://doi.org/10.1037/met0000085

Brose, A., Schmiedek, F., Koval, P., & Kuppens, P. (2015). Emotional inertia contributes to depressive symptoms beyond perseverative thinking. *Cognition and Emotion, 29*, 527–538. https://doi.org/10.1080/02699931.2014.916252

Butler, E. A. (2011). Temporal interpersonal emotion systems: The "TIES" that form relationships. *Personality and Social Psychology Review, 15*, 367–393. https://doi.org/10.1177/1088868311411164

Butler, E. A. (2015). Interpersonal affect dynamics: It takes two (and time) to tango. *Emotion Review, 7*, 336–341. https://doi.org/10.1177/1754073915590622

Butler, E. A., & Randall, A. K. (2013). Emotional coregulation in close relationships. *Emotion Review, 5*, 202–210. https://doi.org/10.1177/1754073912451630

Cabrieto, J., Tuerlinckx, F., Kuppens, P., Hunyadi, B., & Ceulemans, E. (2018). Testing for the presence of correlation changes in a multivariate time series: A permutation based approach. *Scientific Reports, 8*, 1–20. https://doi.org/10.1038/s41598-017-19067-2

Clark, L. A., Watson, D., & Leeka, J. (1989). Diurnal variation in the positive affects. *Motivation and Emotion, 13*, 205–234. https://doi.org/10.1007/BF00995536

Dejonckheere, E., Mestdagh, M., Houben, M., Rutten, I., Sels, L., Kuppens, P., & Tuerlinckx, F. (2019). Complex affect dynamics add limited information to the prediction of psychological well-being. *Nature Human Behaviour, 3*, 478–491. https://doi.org/10.1038/s41562-019-0555-0

Dejonckheere, E., Mestdagh, M., Kuppens, P., & Tuerlinckx, F. (2020). Reply to: Context matters for affective chronometry. *Nature Human Behaviour*, 1–4. https://doi.org/10.1038/s41562-020-0860-7

Dejonckheere, E., Mestdagh, M., Verdonck, S., Lafit, G., Ceulemans, E., Bastian, B., & Kalokerinos, E. K. (2021). The relation between positive and negative affect becomes more negative in response to personally relevant events. *Emotion, 21*, 326–336. https://doi.org/10.1037/emo0000697

Dormann, C., & Griffin, M. A. (2015). Optimal time lags in panel studies. *Psychological Methods, 20*, 489–505. https://doi.org/10.1037/met0000041

Ebner-Priemer, U. W., & Sawitzki, G. (2007). Ambulatory assessment of affective instability in borderline personality disorder: The effect of the sampling frequency. *European Journal of Psychological Assessment, 23*, 238–247. https://doi.org/10.1027/1015-5759.23.4.238

Ebner-Priemer, U. W., Kuo, J., Kleindienst, N., Welch, S. S., Reisch, T., Reinhard, I., Lieb, K., Linehan, M. M., & Bohus, M. (2007). State affective instability in borderline personality disorder assessed by ambulatory monitoring. *Psychological Medicine, 37*(7), 961–970. https://doi.org/10.1017/S0033291706009706

Eisele, G., Vachon, H., Lafit, G., Kuppens, P., Houben, M., Myin-Germeys, I., & Viechtbauer, W. (2020). The effects of sampling frequency and questionnaire length on perceived burden, compliance, and careless responding in experience sampling data in a student population. *Assessment*. https://doi.org/10.1177/1073191120957102

Erbas, Y., Ceulemans, E., Lee Pe, M., Koval, P., & Kuppens, P. (2014). Negative emotion differentiation: Its personality and well-being correlates and a comparison of different assessment methods. *Cognition and Emotion, 28*, 1196–1213. https://doi.org/10.1080/02699931.2013.875890

Erbas, Y., Ceulemans, E., Kalokerinos, E. K., Houben, M., Koval, P., Pe, M. L., & Kuppens, P. (2018). Why I don't always know what I'm feeling: The role of stress in within-person fluctuations in emotion differentiation. *Journal of Personality and Social Psychology, 115*, 179–191. https://doi.org/10.1037/pspa0000126

Erbas, Y., Kalokerinos, E. K., Kuppens, P., van Halem, S., & Ceulemans, E. (2021). Momentary emotion differentiation: The derivation and validation of an index to study within-person fluctuations in emotion differentiation. *Assessment*. https://doi.org/10.1177/1073191121990089

Eronen, M. I., & Bringmann, L. F. (2021). The theory crisis in psychology: How to move forward. *Perspectives on Psychological Science*. https://doi.org/10.1177/1745691620970586

Falkenström, F., Finkel, S., Sandell, R., Rubel, J. A., & Holmqvist, R. (2017). Dynamic models of individual change in psychotherapy process research. *Journal of Consulting and Clinical Psychology, 85*, 537–549. https://doi.org/10.1037/ccp0000203

Farage, M. A., Osborn, T. W., & MacLean, A. B. (2008). Cognitive, sensory, and emotional changes associated with the menstrual cycle: A review. *Archives of Gynecology and Obstetrics, 278*, 299–307. https://doi.org/10.1007/s00404-008-0708-2

Fisher, A. J. (2015). Toward a dynamic model of psychological assessment: Implications for personalized care. *Journal of Consulting and Clinical Psychology, 83*, 825–836. https://doi.org/10.1037/ccp0000026

Fisher, A. J., & Newman, M. G. (2016). Reductions in the diurnal rigidity of anxiety predict treatment outcome in cognitive behavioral therapy for generalized anxiety disorder. *Behaviour Research and Therapy, 79*, 46–55. https://doi.org/10.1016/j.brat.2016.02.006

Fisher, A. J., Bosley, H. G., Fernandez, K. C., Reeves, J. W., Soyster, P. D., Diamond, A. E., & Barkin, J. (2019). Open trial of a personalized modular treatment for mood and anxiety. *Behaviour Research and Therapy, 116*, 69–79. https://doi.org/10.1016/j.brat.2019.01.010

Fisher, A. J., & Bosley, H. G. (2020). Identifying the presence and timing of discrete mood states prior to therapy. *Behaviour Research and Therapy, 128*, 103596. https://doi.org/10.1016/j.brat.2020.103596

Fisher, A. J., Medaglia, J. D., & Jeronimus, B. F. (2018). Lack of group-to-individual generalizability is a threat to human subjects research. *Proceedings of the National Academy of Sciences, 115*, E6106–E6115. https://doi.org/10.1073/pnas.1711978115

Fried, E. I. (2020). Lack of theory building and testing impedes progress in the factor and network literature. *Psychological Inquiry, 31*, 271–288. https://doi.org/10.1080/1047840X.2020.1853461

Fisher, A. J., Reeves, J. W., Lawyer, G., Medaglia, J. D., & Rubel, J. A. (2017). Exploring the idiographic dynamics of mood and anxiety via network analysis. *Journal of Abnormal Psychology, 126*, 1044–1056. https://doi.org/10.1037/abn0000311

Galili-Weinstock, L., Lazarus, G., Atzil-Slonim, D., Bar-Kalifa, E., Rafaeli, E., & Peri, T. (2020). Self-compassion among psychotherapy clients is in the details of negative, not positive, emotions. *The Journal of Positive Psychology*, 1–10. https://doi.org/10.1080/17439760.2019.1627396

Golder, S. A., & Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science, 333*, 1878–1881. https://doi.org/10.1126/science.1202775

Hamaker, E. L., & Wichers, M. (2017). No time like the present: Discovering the hidden dynamics in intensive longitudinal data. *Current Directions in Psychological Science, 26*, 10–15. https://doi.org/10.1177/0963721416666518

Haslbeck, J. M. B., Ryan, O., Robinaugh, D., Waldorp, L., & Borsboom, D. (2019, December 10). Modeling psychopathology: From data models to formal theories. https://doi.org/10.31234/osf.io/jgm7f.

Hengartner, M. P., Kruger, T. H., Geraedts, K., Tronci, E., Mancini, T., Ille, F., et al. (2017). Negative affect is unrelated to fluctuations in hormone levels across the menstrual cycle: Evidence from a multisite observational study across two successive cycles. *Journal of Psychosomatic Research, 99*, 21–27. https://doi.org/10.1016/j.jpsychores.2017.05.018

Hollenstein, T. (2015). This time, it's real: Affective flexibility, time scales, feedback loops, and the regulation of emotion. *Emotion Review, 7*, 308–315. https://doi.org/10.1177/1754073915590621

Houben, M., Mestdagh, M., Dejonckheere, E., Obbels, J., Sienaert, P., van Roy, J., & Kuppens, P. (2020). The statistical specificity of emotion dynamics in borderline personality disorder. *Journal of Personality Disorders.* https://doi.org/10.1177/1754073915590621

Houben, M., Van Den Noortgate, W., & Kuppens, P. (2015). The relation between short-term emotion dynamics and psychological well-being: A meta-analysis. *Psychological Bulletin, 141*, 901–930. https://doi.org/10.1037/a0038822

Jacobson, N. C., Chow, S. M., & Newman, M. G. (2019). The Differential Time-Varying Effect Model (DTVEM): A tool for diagnosing and modeling time lags in intensive longitudinal data. *Behavior Research Methods, 51*, 295–315. https://doi.org/10.3758/s13428-018-1101-0

Jebb, A. T., Tay, L., Wang, W., & Huang, Q. (2015). Time series analysis for psychological research: Examining and forecasting change. *Frontiers in Psychology, 6*, 727. https://doi.org/10.3389/fpsyg.2015.00727

Kalokerinos, E. K., Résibois, M., Verduyn, P., & Kuppens, P. (2017). The temporal deployment of emotion regulation strategies during negative emotional episodes. *Emotion, 17*, 450–458. https://doi.org/10.1037/emo0000248

Koval, P., & Kuppens, P. (2012). Changing emotion dynamics: Individual differences in the effect of anticipatory social stress on emotional inertia. *Emotion, 12*, 256–267. https://doi.org/10.1037/a0024756

Koval, P., Pe, M. L., Meers, K., & Kuppens, P. (2013). Affect dynamics in relation to depressive symptoms: Variable, unstable or inert? *Emotion, 13*, 1132. https://doi.org/10.1037/a0033579

Kuppens, P. (2015). It's about time: A special section on affect dynamics. *Emotion Review, 7*, 297–300. https://doi.org/10.1177/1754073915590947

Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010a). Emotional inertia and psychological maladjustment. *Psychological Science, 21*, 984–991. https://doi.org/10.1177/0956797610372634

Kuppens, P., Oravecz, Z., & Tuerlinckx, F. (2010b). Feelings change: Accounting for individual differences in the temporal dynamics of affect. *Journal of Personality and Social Psychology, 99*, 1042–1060. https://doi.org/10.1037/a0020962

Lapate, R. C., & Heller, A. S. (2020). Context matters for affective chronometry. *Nature Human Behaviour, 4*, 688–689. https://doi.org/10.1038/s41562-020-0860-7

Larsen, R. J. (1987). The stability of mood variability: A spectral analytic approach to daily mood assessments. *Journal of Personality and Social Psychology, 52*, 1195–1204.

Lazarus, G., Atzil-Slonim, D., Bar-Kalifa, E., Hasson-Ohayon, I., & Rafaeli, E. (2019). Clients' emotional instability and therapists' inferential flexibility predict therapists' session-by-session empathic accuracy. *Journal of Counseling Psychology, 66*, 56–69. https://doi.org/10.1037/cou0000310

Liu, Y., & West, S. G. (2016). Weekly cycles in daily report data: An overlooked issue. *Journal of Personality, 84*, 560–579. https://doi.org/10.1111/jopy.12182

Mneimne, M., Fleeson, W., Arnold, E. M., & Furr, R. M. (2018). Differentiating the everyday emotion dynamics of borderline personality disorder from major depressive disorder and bipolar disorder. *Personality Disorders, 9*, 192–196. https://doi.org/10.1037/per0000255

Molenaar, P. C. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement, 2*, 201–218. https://doi.org/10.1207/s15366359mea0204_1

Molenaar, P. C., & Campbell, C. G. (2009). The new person-specific paradigm in psychology. *Current Directions in Psychological Science, 18*, 112–117. https://doi.org/10.1111/j.1467-8721.2009.01619.x

Murray, G., Nicholas, C. L., Kleiman, J., Dwyer, R., Carrington, M. J., Allen, N. B., & Trinder, J. (2009). Nature's clocks and human mood: The circadian system modulates reward motivation. *Emotion, 9*, 705–716. https://doi.org/10.1037/a0017080

Neubauer, A. B., & Schmiedek, F. (2020). Studying within-person variation and within-person couplings in intensive longitudinal data: Lessons learned and to be learned. *Gerontology, 66*, 332–339. https://doi.org/10.1159/000507993

Pascual-Leone, A., & Greenberg, L. S. (2007). Emotional processing in experiential therapy: Why "the Only Way Out Is Through". *Journal of Consulting and Clinical Psychology, 75*, 875–887. https://doi.org/10.1037/0022-006X.75.6.875

Piccirillo, M. L., & Rodebaugh, T. L. (2019). Foundations of idiographic methods in psychology and applications for psychotherapy. *Clinical Psychology Review, 71*, 90–100. https://doi.org/10.1016/j.cpr.2019.01.002

Ram, N., Chow, S.-M., Bowles, R. P., Wang, L., Grimm, K., Fujita, F., & Nesselroade, J. R. (2005). Examining interindividual differences in cyclicity of pleasant and unpleasant affects using spectral analysis and item response modeling. *Psychometrika, 70*, 773–790. https://doi.org/10.1007/s11336-001-1270-5

Santangelo, P. S., Limberger, M. F., Stiglmayr, C., Houben, M., Coosemans, J., Verleysen, G., Kuppens, P., Tuerlinckx, F., Vanpaemel, W., & Ebner-Priemer, U. W. (2016). Analyzing subcomponents of affective dysregulation in borderline personality disorder in comparison to other clinical groups using multiple e-diary datasets. *Borderline Personality Disorder and Emotion Dysregulation, 3*, 1–13. https://doi.org/10.1186/s40479-016-0039-z

Scargle, J. D. (1982). Studies in astronomical time series analysis. II-Statistical aspects of spectral analysis of unevenly spaced data. *The Astrophysical Journal, 263*, 835e853.

Song, J., Howe, E., Oltmanns, J. R., & Fisher, A. J. (2021). *Examining the predictive validity of single items in ecological momentary assessments*. Department of Psychology, University of California, Berkeley.

Thompson, R. J., Mata, J., Jaeggi, S. M., Buschkuehl, M., Jonides, J., & Gotlib, I. H. (2012). The everyday emotional experience of adults with major depressive disorder: Examining emotional instability, inertia, and reactivity. *Journal of Abnormal Psychology, 121*, 819–829. https://doi.org/10.1037/a0027978

Trull, T. J., & Ebner-Priemer, U. W. (2020). Ambulatory assessment in psychopathology research: A review of recommended reporting guidelines and current practices. *Journal of Abnormal Psychology, 129*, 56–63. https://doi.org/10.1037/abn0000473

Trull, T. J., Lane, S. P., Koval, P., & Ebner-Priemer, U. W. (2015). Affective dynamics in psychopathology. *Emotion Review, 7*(4), 355–361. https://doi.org/10.1177/1754073915590617

van de Maat, R., Lataster, J., & Verboon, P. (2020). Why and how to deal with diurnal cyclic patterns in ambulatory assessment of emotions. *European Journal of Psychological Assessment.* https://doi.org/10.1027/1015-5759/a000579

van der Gucht, K., Dejonckheere, E., Erbas, Y., Takano, K., Vandemoortele, M., Maex, E., Raes, F., & Kuppens, P. (2019). An experience sampling study examining the potential impact of a mindfulness-based intervention on emotion differentiation. *Emotion, 19*, 123–131. https://doi.org/10.1037/emo0000406

Verduyn, P., Delvaux, E., Van Coillie, H., Tuerlinckx, F., & Van Mechelen, I. (2009). Predicting the duration of emotional experience: Two experience sampling studies. *Emotion, 9*, 83–91. https://doi.org/10.1037/a0014610

Wang, L. P., & Maxwell, S. E. (2015). On disaggregating between-person and within-person effects with longitudinal data using multilevel models. *Psychological Methods, 20*, 63–83. https://doi.org/10.1037/met0000030

Wehr, T. A. (2018). Bipolar mood cycles and lunar tidal cycles. *Molecular Psychiatry, 23*, 923–931. https://doi.org/10.1038/mp.2016.263

Wendt, L. P., Wright, A. G., Pilkonis, P. A., Woods, W. C., Denissen, J. J., Kühnel, A., & Zimmermann, J. (2020). Indicators of affect dynamics: Structure, reliability, and personality correlates. *European Journal of Personality, 34*, 1060–1072. https://doi.org/10.1002/per.2277

Wright, A. G. C., & Zimmermann, J. (2019). Applied ambulatory assessment: Integrating idiographic and nomothetic principles of measurement. *Psychological Assessment, 31*, 1467–1480. https://doi.org/10.1037/pas0000685

Wright, A. G., & Woods, W. C. (2020). Personalized models of psychopathology. *Annual Review of Clinical Psychology, 16*, 49–74. https://doi.org/10.1146/annurev-clinpsy-102419-125032

Yarkoni, T. (2020). The generalizability crisis. *Behavioral and Brain Sciences*, 1–37. https://doi.org/10.1017/S0140525X20001685

Chapter 6
Affect Dynamics and Time Scales: Pictures of Movies

Tom Hollenstein

Abstract The study of affect dynamics is very much like trying to infer the movies of people's emotional lives from random photographs or brief clips. In this chapter, I consider the domain of variability of affect in terms of the dynamics of change inferred from sequences of observations. Specifically, through consideration of time scales, I offer a challenge to some of the interpretive lenses that have been applied to affective variability data as attempts to describe movies from clips and/or photographs. I first consider the limitations of real-time dynamics and then grapple with the longer timescale of affect dynamics examined through experience sampling methods, as these have come under the most scrutiny in the past few years. The conclusion includes recommendations as to how to proceed with research in this domain with these inferential limitations in mind.

6.1 Introduction

Imagine that instead of seeing the full movie of Star Wars for the first time that you saw only a 2-min scene or a random handful of pictures. Perhaps the clip was only of C3PO and R2D2 lost in the desert; from that you might infer that Star Wars was an android buddy movie. Alternatively, your handful of still pictures might only consist of scenes of Luke and Leia alone and with each other, from which you may conclude that this was a sci-fi romance movie. Of course, you might only get pictures of spaceships firing lasers at each other and conclude this was an adaptation of a video game. Even with a smattering of androids, young romance, and sci-fi action clips or photos, it would be difficult to infer the plot and quality of the movie without the continuous flow, narrative arc, and most importantly the variability across the sequence of scenes. When we are trying to understand the movies that are the continuous stream of peoples' emotional lives, their moment-to-moment existence,

T. Hollenstein (✉)
Department of Psychology, Queen's University, Kingston, ON, Canada
e-mail: Tom.Hollenstein@queensu.ca

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_6

we can run into the same problems: limited sampling over time and a lack of temporal adjacency that limit interpretations.

In this chapter, I consider the domain of variability of affect in terms of the dynamics of change inferred from sequences of observations. Specifically, through consideration of time scales, I offer a challenge to some of the interpretive lenses that have been applied to affective variability data as attempts to describe movies from clips and/or photographs. I will begin by considering the limitations of real-time dynamics. Then, I will grapple with the longer timescale of affect dynamics examined through experience sampling methods, as these have come under the most scrutiny in the past few years. I will ultimately conclude with recommendations as to how to proceed with research in this domain.

6.2 Real Time

The advent of accessible video technology in the 1970s and 1980s led to a flurry of observational studies of emotions in naturalistic contexts. Developmental scientists in particular have relied heavily on observational coding from video, although this has also been a mainstay for most dyadic interaction research (e.g., Gottman et al., 1995). From this, many emotional processes across the lifespan have been catalogued to become the basis of developmental and social theories such as Attachment Theory (Ainsworth, 1978) and Coercion Theory (Patterson, 2016), as well as non-developmental approaches including mathematical theories of marriage (Gottman et al., 2005) and Temporal Interpersonal Emotion Systems (Butler, 2011; Lougheed, 2020). In all, the theorized mechanisms underlying the formation of behavioral tendencies or relationship patterns are moment-to-moment processes. Deemed *real-time dynamics*, these mechanisms shape biological and behavioral adaptations, increasing the probability that some patterns will recur in the future and others will dissipate (Granic et al., 2016; Hollenstein, 2015; Lavelli & Fogel, 2013; Lewis, 2011; Lougheed, 2020; Witherington & Boom, 2019). However, mapping these theoretical claims to observed behavior, particularly affective processes, has been a daunting empirical challenge of the past several decades (Granic & Hollenstein, 2003; Lougheed & Hollenstein, 2018).

To bridge this theory-method gulf, one dominant approach has been to record real-time emotional expressions via observational coding systems such as the Facial Affect Coding System (FACS; Ekman & Friesen, 1978), the Specific Affect Coding System and variants (Gottman et al., 1995; Granic et al., 2007; Lougheed & Hollenstein, 2014), or Living in Family Environments coding system (LIFE; Hops et al., 1995). While these approaches were originally developed to capture the *content* of observable affect (e.g., frequencies of anger expressions), they have also afforded examinations of the *structure* (i.e., dynamic patterns) within these time series (Granic & Hollenstein, 2003). To briefly summarize, two of these approaches have converged on similar dynamic characteristics that reflect the ability to move in and out of affective states. Consistent with the persistence of negative emotions seen in certain clinical disorders (e.g., Kashdan & Rottenberg, 2010), individual's relative inertia (e.g., autocorrelation) of affective states has been associated with depression (Kuppens et al., 2010, 2012). Using a dynamic systems conceptualization, a second approach has shown that dyadic rigidity (e.g., fewer transitions among states, restricted range of states) is associated with anxiety, depression, and externalizing problems (e.g., Granic et al., 2007; Lougheed & Hollenstein, 2016; van der Giessen et al., 2015; van der Giessen & Bögels, 2018). Thus, changing in and out of affective states moment-to-moment during quasi-natural emotional situations appears to be a hallmark of adaptive functioning (Hollenstein, 2015).

Nonetheless, real-time approaches rely on several assumptions and methodological pragmatics that limit the interpretations that may be warranted. First, often for very important ethical reasons, these methods elicit emotions in a somewhat contrived fashion. With real-time designs, participants are instructed to think about or discuss problems or emotions. For example, dyads in close relationships are often asked to identify the topics they are most likely to fight about, which then becomes the topic that experimenters ask them discuss later in front of the cameras. While this increases the probability that participants will become emotionally engaged, these interactions may lack sufficient intensity and/or the spontaneous rise and fall of emotion that we wish to infer. Moreover, this may be most problematic in normative or convenience samples with participants who are not particularly prone to particularly intense emotions or expression. Thus, some of the variance detected by restricted range, few transitions, and high autocorrelations may not be due to the putative processes of dysfunction but the ethical constraints of the methodology.

Second, for pragmatic reasons, these snapshots of naturalistic occurrences of affect dynamics are brief, lasting no more than 10–20 min at most. Between-subject differences are interpreted as evidence of what the other 23+ h of the day might be like. Despite some of the categorization accuracy proclaimed by a "thin slice" approach (i.e., identification of diagnostic status via brief clips or phots; see Slepian et al., 2014), the deeper inference about affective dynamics that we wish to make is that these captured moments are consistent with participants' real world experiences, that they reflect the ongoing processes which explain individual differences. Thus, framed within this chapter's movie metaphor, these real-time observations are akin to seeing a brief clip of a 2-h movie. Did we capture the cantina scene, death of Obi Wan, or Luke home with his Aunt and Uncle? Was that 5-min discussion indicative of how these individuals typical express their emotions?

The first two issues are related to the third issue. Most often affect dynamics are compared between typical and atypical groups, rarely across a full spectrum. As a result, affective variation in typical samples may be quite compressed compared to atypical samples with extreme emotional dysregulation. It is difficult to disentangle whether these differences are due to a relative ease in which emotions are elicited in the lab, rather than the dynamic patterns themselves. Thus, if we only take a snapshot, we are more likely to capture emotional intensity in extreme groups.

Fourth, one-time observations may reflect variability due to the novelty of the contrived emotion-eliciting situation. Indeed, it is rare for research studies to be able to afford a warm up or practice session. When they do, as with longitudinal studies, there can be differences across sessions. However, it is unclear whether longitudinal change is always due to time, development, etiology, etc. or occasion-specific error. It is rare to have identical real-time observations occur within a short time span (e.g., two 1 h observation sessions within a week or two), but when they do, the results indicate a need to consider the reliability of our inferences. For example, there is a phenomenon noted in parent-child interaction research called the “first session effect” (Snyder & Stoolmiller, 2002). When trying to capture dynamics related to parenting across a wide range of dyads, high functioning dyads tend to be more emotionally restrained during the first lab visit than on subsequent occasions (Snyder et al., 2003). Further, test-retest reliabilities of affect dynamics tend to be good but relatively modest (e.g., around $r = .5$; Hollenstein et al., 2004). Thus, one-time snapshots may underestimate affective dynamics that occur in real life.

Finally, the reliance on the dyad can be an inference problem for several reasons. While reasonably justified by systems-oriented theory and/or the fact that emotions typically arise in a social or relational context (Butler, 2011), what we observe in a specific dyad may be specific to that dyad. This is especially concerning when, in virtually every study, the associations, predictions, or explanations are about an *individual* dyad member’s functioning or well-being. One approach has been to depict the dynamics of an individual, ignoring the dynamic contribution by other interaction partners, to predict or to differentiate by outcomes (e.g., Kuppens et al., 2010). In my own line of research, we have framed the dynamics we observe as characteristic of the dyadic system (Granic & Hollenstein, 2003, 2006; Hollenstein, 2012). Yet, with rare exceptions (e.g., predicting relationship quality; Lougheed & Hollenstein, 2016), we have analyzed dyadic flexibility in relation to each individual’s mental health symptoms (e.g., Hollenstein et al., 2004; Lougheed & Hollenstein, 2016; van der Giessen et al., 2015). To complicate matters further, when we have examined individual versus dyadic dynamics, the dyadic indices have been stronger predictors of subsequent mental health of each dyad member than their individual flexibility indices (van der Giessen et al., 2015). Thus, we are caught in a vicious circle of methodology. In order to capture real-time dynamics, interactions with others are the best source for tapping into the temporal flow; yet the patterns that emerge depend a great deal on which interaction partner (e.g., their history, power dynamic, etc.) and the nature and timing of the task (e.g., is this a new conflict or an old one). To whom and to what can we generalize?

Taken together, the problems and limitations identified here are the result of carefully considered research decisions, constrained by ethics, resources, and pragmatics. Nonetheless, they present a critical ceiling on the scope of our inferences and generalizability of findings. On the one hand, these real-time approaches allow for true dynamic analysis of moment-to-moment transitions. The range of analytical techniques applied to these data grows every year (e.g., Lougheed et al., 2019, 2020; Yang et al., 2019). However, until we go beyond the limits of brief movie clips, we will not be able to infer the movie as well as we need to.

Amid this backdrop of the video-based observational approach to real-time dynamics, the emergence of mobile technologies has produced an alternative. Perhaps by taking the intensive longitudinal approach at longer time scales we would have a better vantage point to understand the vicissitudes of affect as they occur in people’s real lives. This potential to capture a more accurate portrayal of real-world affect dynamics has driven an exponential rise in ambulatory methods. Starting slowly with pagers (e.g., Larson & Csikszentmihalyi, 1983) and palm pilots (Gruber et al., 2013), the arrival of the ubiquitous smart phone opened up this option on a grand scale (see chapters in this volume). As a result, there is now a large body of work on affect dynamics based on daily experiences over hours, days, and weeks.

6.3 Daily Experiences

Over the past decade or more, the affordances of digital and mobile technology has led to an explosion of intensive longitudinal data. Affective scientists in particular have found the ability to tap into the momentary experiences of individuals a useful lens to understand emotional functioning in novel ways. There was the hope that it would transcend the problems of retrospective and trait-like self-report as well as the limitations of lab-based observations. Study designs range from one sample a day to up to a dozen or more per day, and extend to several days to several weeks of repeated daily measurement. Thus, these experience studies are not capturing variation in real time but at longer, diurnal time scales. Across studies, lower variability in affect has been associated with greater well-being, whereas greater variability has been associated with a range of problems and pathologies such as neuroticism, borderline personality disorder, bipolar disorder, posttraumatic stress disorder, anxiety, and depression (Eldesouky et al., 2018; Houben et al., 2015; Kashdan et al., 2006; Miller & Pilkonis, 2006; Pfaltz et al., 2010). Thus, the general conclusion has been that "emotional lability," operationalized as diurnal affect dynamics, may be a transdiagnostic factor linking emotions to various manifestations of pathology.

Over the past few years, however, this proliferation of empirical findings on affect dynamics has been met with some more robust re-evaluation (e.g., Brose et al., 2020; Dejonckheere et al., 2019; Kalokerinos et al., 2020). Before expanding upon the explanations offered in these critiques, let me first applaud these and other authors for the due diligence and self-correction that engenders robust scientific practice. For example, Dejonckheere et al. (2019) analyzed data from 15 studies, comparing 16 different measures of affect dynamics. None of these predicted well-being or psychopathology after controlling for mean levels of negative or positive affect. They conclude "[o]ur findings indicate that conventional emotion research is currently unable to demonstrate independent relations between affect dynamics and psychological well-being." (Dejonckheere et al., 2019; p. 478). That is a bold statement, especially coming from researchers who have built their careers at the forefront of the affect dynamics field.

Several kinds of explanations for these recent findings have been offered. To a one, these meta- and re-analyses portray the problem as a failure to control for the more basic central tendency measures, which, once included, wipe out the variability or dynamic effects. Thus, the concerns are mostly methodological: measurement reliability, floor effects (especially in community samples), the frequency within days and total number of days of sampling, the need for greater precision, confusion about within- and between-person variability, and even doubts about the nature and measurement of the symptom and well-being outcomes themselves (Brose et al., 2020; Dejonckheere et al., 2019; Kalokerinos et al., 2020). I will not reiterate these here and will just point the reader to those original papers. However, a problem only mentioned briefly in these accounts (if at all) is the disconnect between the real-world phenomena trying to be captured and the means used to do so. In short, using pictures to infer a movie. As I did with real-time dynamics above, here I will expound upon these time scale issues in an attempt to highlight further considerations of diurnal affect "dynamics". Specifically, these issues will be summarized under two general categories of affect and transitions.

6.3.1 Affect

Affect is an umbrella term covering mood, stress, and emotions (Gross, 2015). As a result, there is quite a bit of variety in how affect dynamics have been conceptualized and measured. Ambiguous distinctions between mood, stress, and emotions further fuels an expansive interpretative lens. For example, emotions are more rapid responses to the immediate situation but moods, by definition, transpire at longer time scales (Lewis, 2000). Thus, changes over time in mood may have different parameters and meaning than changes in emotions over the same time intervals.

Most often, however, affect is measured through valence, either on a positive to negative continuum or as separate positive and negative scales. While this has the advantage of convenience (e.g., easy for participants to report), this approach comes with several problems. First, there is the inherent judgment about emotions in such reports that feeling anger or sadness or being in a low energy mood are "bad" or negative. Thus, negativity is either a researcher-driven label (e.g., latent factor) or respondents using a valence scale may be reporting as much about their own judgments of negativity as the intensity of the feelings. Second, it may not be clear to the respondent (or researcher) whether valence is capturing mood or emotion. Third, the dynamics being captured are variations in reports on an interval scale (e.g., 1–10 or 1–100), not shifts between distinctive states. Indeed, these valence measures neglect specific emotional states, each of which has different characteristics and, most relevant to dynamics, different time courses (e.g., sadness unfolds more slowly than flashes of anger). Like other psychological measures, this compromises interpretations of units of affect—is the difference between 1 and 2 the same as between 9 and 10? Is this difference the same for all individuals? Thus, taken together, it is difficult for this measurement approach to clearly match theorized phenomena (e.g., emotion/mood/affect lability). However, regardless of the measurement format, there is also the issue of temporal non-adjacency or a lack of actual transitions that is considered next.

6.3.2 Transitions

The basis of connecting affect dynamics with psychopathology is through affect—emotion, mood, or stress—lability. Affect lability (sometimes termed instability) is defined in a variety of ways, such as "abnormally frequent, intense, and wide ranging changes in affective states" (Contardi et al., 2018) or "frequent and intense fluctuations in emotion" Thompson et al., 2011). Thus, qualitative clinical observations and the diagnostic characteristics that have arisen from them are fundamentally characterized by *temporally adjacent shifts or* transitions from one moment to the next in affective states (e.g., sadness, anger, fear).

Given these characterizations, real-time observations are better able to capture the theorized dynamics, the previously noted limitations notwithstanding, than experience sampling. Mobile sampling necessarily transpires with time intervals of various durations, typically an hour or more, between samples. Even with up to 20 samples per day in some studies, none have the capacity to actually tap into transitions of affect. Yet this is how the variability of ESM studies is generally interpreted, especially when contrasting diagnostic groups.

Finally, the consideration of transitions in affect dynamics may also speak to the recent findings that affect dynamic effects are negated by mean levels (Brose et al., 2020; Dejonckheere et al., 2019; Kalokerinos et al., 2020). It is possible that this mean-to-variability relation is a simple artifact of the selective sampling of a continuous time series (i.e., pictures of movies). Schiepek and colleagues (Schiepek et al., 2016) have illustrated this elegantly in their work in which they obtain daily measurement from inpatient groups. As shown in Fig. 6.1, the actual changes throughout a day if measured continuously (i.e., the movie) are shown in Panel A. Each subsequent Panel B-F reflects successively fewer samples. The dynamics appear to get more and more stable as the number of measurement points decreases.

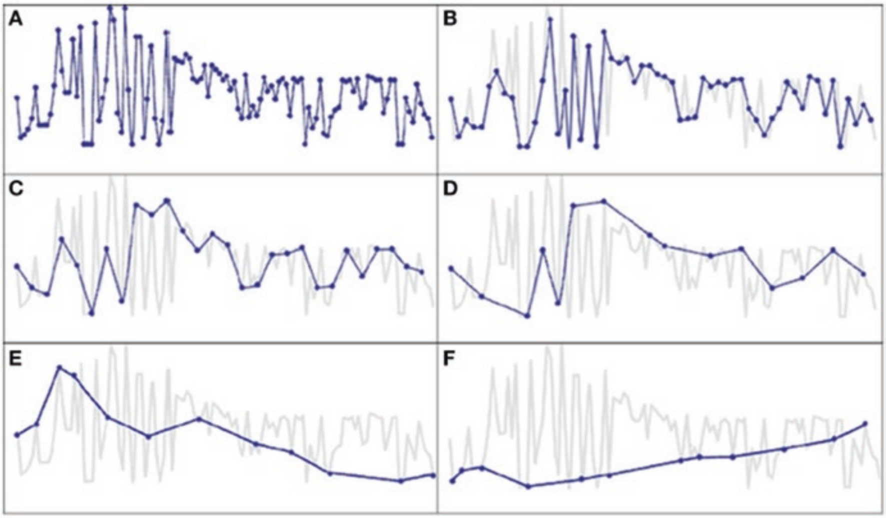


Fig. 6.1 Illustration of the smoothing of sample-to-sample changes in time series as the number of samples decreases. The original time series (e.g., affect fluctuations moment-to-moment for an individual) is in Panel **A**. As the number of measurement samples decreases across Panels **B** through **F**, the variability decreases and the plot of successive measurement samples becomes more flat. Used by Permission from Schiepek et al. (2016)

Importantly, this visual representation reveals why the mean may be a more predictive parameter than variability indices. More specifically, it shows that with less than full sampling the mean can easily wipe out any variability effects. Furthermore, this suggests that the degree to which the mean is a better predictor than variability indices may be a function of the size of the interval between samples—shorter intervals or more frequent samples should provide more unique variability information than longer intervals or less frequent sampling.

6.4 Conclusions

I have identified a few of the issues surrounding the field of affect dynamics, particularly those limitations that impede our theoretical interpretations, at the two primary time scales at which this research is done. To conclude I will consider broader implications and suggest a few possibilities for future research.

6.4.1 Dynamic or Variable?

In the social sciences, we often borrow concepts and use metaphors from other disciplines. The concept of dynamics is a great example. Formally, the term dynamic refers to change over time, which presumes the ability to detect change as it happens. If we are not measuring continuously in order to capture transitions when they happen, does it make sense to call variability across non-adjacent samples *dynamic*? At best it is aspirational, as it is certainly the temporal structure of real-world phenomena we are trying to comprehend, yet we often sample at intervals such that transitional *change* cannot be detected directly. In these cases, we certainly have variability, but perhaps not dynamics. Moreover, while this is mostly a concern for experience sampling studies, even many observational studies that have the opportunity for continuous real-time measurement rely on either event-occurrence coding or arbitrary time bins of 10 s or more. Thus, I propose stricter construal of affect "dynamics", situated as a subset of affect variability that *requires* temporal adjacency of measurement sequences. This would leave only real-time and continuous measurement as affording possible dynamic interpretations.

6.4.2 Dynamics and Intensity

Although the problems of mean levels of affect with respect to dynamics has been shown at longer time scales, real-time dynamics are likely no less immune. First, theoretically intensity should drive dynamics. For example, a recent study found that infants' physiological arousal inertia was critically elevated at extreme intensities but not at average levels of arousal (Wass et al., 2020). Physiologically, this is also seen in heart rate variability indices that decrease precipitously in the face of emotional intensity (Beauchaine, 2001). Given the strong connection between intensity of feelings and autonomic arousal, this may be the case for behavioral expressions of emotion as well. Thus, it is plausible that observations of real-time dynamics of affective states may reflect individual differences in emotional intensity.

Second, similar to the problems encountered in theoretical tests of emotional concordance (Hollenstein & Lanteigne, 2014), emotional intensity in our standard laboratory designs is unlikely to be high. Thus, we may only be able to generalize these findings to low intensity situations. This may also be the reason that we have found that individual differences in real-time dynamics (i.e., the micro level of the Flex3 model; Hollenstein et al., 2013) correspond to well-being but context-to-context flexibility (i.e., the meso level of the Flex3 model) does not (Lougheed & Hollenstein, 2016). This problem could be resolved with comparisons of groups who tend to have low and high intensity emotions. For example, lower flexibility is associated with anxiety (van der Giessen & Bögels, 2018), depression (van der Giessen et al., 2015), and externalizing problems (Granic et al., 2007). However, expression but not intensity was measured in these studies, so it remains an open question as to whether flexibility was distinct from intensity.

For those of us who focus on real-time dynamics in particular, it is time to grapple with intensity with the same self-correcting rigor as has been done with experience sampling (Brose et al., 2020; Dejonckheere et al., 2019; Kalokerinos et al., 2020). Accounting for mean levels of intensity in models of flexibility and other dynamics is a necessary next step. Given the temporal adjacency of real-time measurement, it is possible that these approaches are less sensitive, as Schiepek et al. (2016) observed. Nevertheless, this is untested yet necessary for the field to rely on.

6.4.3 Multiple Time Scales

Although much of the affect dynamics literature assumes a correspondence across time scales, this has not been tested directly. Theoretically, adaptations day-to-day should relate to the adaptations that occur hour-to-hour, minute-to-minute, and second-to-second. For example, I have argued that real-time flexibility—direct, temporally adjacent shifts from one emotional state to another—reflects emotion regulation skills (Hollenstein, 2015). By implication then, mechanisms at shorter time scales, such as inhibitory and attentional control (e.g., Twivy et al., 2020), should support these regulatory capacities. Further, greater real-time flexibility should correspond to flexible day-to-day adaptations at longer time scales. Thus, we need studies designed with vertical integration across time scales and develop the methods to analyze them (e.g., Multiple time-scale multiphase latent basis growth modeling; Helm et al., 2016).

In conclusion, as we strive to improve our understanding of affect dynamics, it is easy to forget about the challenging limitations that plague our research. I know that in my own research, I often feel like the protagonist in the story of the professor looking for his keys:

> *A graduate student emerges from the university building where she works to find her professor looking around the parking lot underneath one of the street lamps. She asks the professor, "What are you looking for?"*
>
> *"My keys," he says.*
>
> *"Where did you lose them?"*
>
> *The professor points into the dark corner of the parking lot nearer to his car, "Over there."*
>
> *Puzzled, the graduate student suggested, "Well, then why don't you look over there where you dropped them?"*
>
> *"Because the light is better over here!"*

Barring some technological breakthrough, we may only ever get still photos and short clips of the movies of people's lives we wish to understand. That's ok. We have learned a great deal and will continue to do so. At the same time, it is important to acknowledge our limitations and concede that we may not ever know the full plot.

References

Ainsworth, M. D. S. (1978). The Bowlby-Ainsworth attachment theory. *Behavioral and Brain Sciences, 1*(3), 436–438. https://doi.org/10.1017/S0140525X00075828

Beauchaine, T. (2001). Vagal tone, development, and Gray's motivational theory: Toward an integrated model of autonomic nervous system functioning in psychopathology. *Development and Psychopathology, 13*(2), 183–214. https://doi.org/10.1017/S0954579401002012

Brose, A., Schmiedek, F., Gerstorf, D., & Voelkle, M. C. (2020). The measurement of within- person affect variation. *Emotion, 20*(4), 677. https://doi.org/10.1037/emo0000583

Butler, E. A. (2011). Temporal interpersonal emotion systems: The "TIES" that form relationships. *Personality and Social Psychology Review, 15*(4), 367–393. https://doi.org/10.1177/1088868311411164

Contardi, A., Imperatori, C., Amati, I., Balsamo, M., & Innamorati, M. (2018). Assessment of affect lability: Psychometric properties of the ALS-18. *Frontiers in Psychology, 9*, 427. https://doi.org/10.3389/fpsyg.2018.00427

Dejonckheere, E., Mestdagh, M., Houben, M., Rutten, I., Sels, L., Kuppens, P., & Tuerlinckx, F. (2019). Complex affect dynamics add limited information to the prediction of psychological well-being. *Nature Human Behaviour, 3*(5), 478–491. https://doi.org/10.1038/s41562-019-0555-0

Ekman, P., & Friesen, W. (1978). *The facial action coding system*. Consulting Psychologists' Press.

Eldesouky, L., Thompson, R. J., Oltmanns, T. F., & English, T. (2018). Affective instability predicts the course of depression in late middle-age and older adulthood. *Journal of Affective Disorders, 239*, 72–78. https://doi.org/10.1016/j.jad.2018.06.038

Gottman, J. M., McCoy, K., Coan, J., & Collier, H. (1995). *The Specific Affect Coding System (SPAFF) for observing emotional communication in marital and family interaction*. Erlbaum.

Gottman, J. M., Murray, J. D., Swanson, C. C., Tyson, R., & Swanson, K. R. (2005). *The mathematics of marriage: Dynamic nonlinear models*. MIT Press.

Granic, I., & Hollenstein, T. (2003). Dynamic systems methods for models of developmental psychopathology. *Development and Psychopathology, 15*, 641–669. https://doi.org/10.1017/s0954579403000324

Granic, I., & Hollenstein, T. (2006). A survey of dynamic systems methods for developmental psychopathology. In D. Cicchetti (Ed.), *Developmental psychopathology* (2nd ed.). Wiley.

Granic, I., Hollenstein, T., & Lichtwarck-Aschoff, A. (2016). A survey of dynamic systems methods for developmental psychopathology. In D. Cicchetti (Ed.), *Developmental psychopathology* (3rd ed., pp. 717–759). Wiley.

Granic, I., O'Hara, A., Pepler, D., & Lewis, M. D. (2007). A dynamic systems analysis of parent–child changes associated with successful "real-world" interventions for aggressive children. *Journal of Abnormal Child Psychology, 35*(5), 845–857. https://doi.org/10.1007/s10802-007-9133-4

Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological Inquiry, 26*(1), 1–26. https://doi.org/10.1080/1047840X.2014.940781

Gruber, J., Kogan, A., Mennin, D., & Murray, G. (2013). Real-world emotion? An experience-sampling approach to emotion experience and regulation in bipolar I disorder. *Journal of Abnormal Psychology, 122*(4), 971–983. https://doi.org/10.1037/a0034425

Helm, J. L., Ram, N., Cole, P. M., & Chow, S. M. (2016). Modeling self-regulation as a process using a multiple time-scale multiphase latent basis growth model. *Structural Equation Modeling: A Multidisciplinary Journal, 23*(5), 635–648. https://doi.org/10.1080/10705511.2016.1178580

Hollenstein, T. (2012). The dynamic systems perspective: What is the system? In L. C. Mayes & M. Lewis (Eds.), *The Cambridge handbook of environment in human development* (pp. 138–151). Cambridge University Press.

Hollenstein, T. (2015). This time, it's real: Affective flexibility, time scales, feedback loops, and the regulation of emotion. *Emotion Review, 7*, 308–315. https://doi.org/10.1177/1754073915590621

Hollenstein, T., Granic, I., Stoolmiller, M., & Snyder, J. (2004). Rigidity in parent-child interactions and the development of externalizing and internalizing behavior in early childhood. *Journal of Abnormal Child Psychology, 32*, 595–607. https://doi.org/10.1023/B:JACP.0000047209.37650.41

Hollenstein, T., & Lanteigne, D. (2014). Models and methods of emotional concordance. *Biological Psychology, 98*, 1–5. https://doi.org/10.1016/j.biopsycho.2013.12.012

Hollenstein, T., Lichtwarck-Aschoff, A., & Potworowski, G. (2013). A model of socio-emotional flexibility at three time scales. *Emotion Review, 5*, 397–405. https://doi.org/10.1177/1754073913484181

Hops, H., Biglan, A., Tolman, A., Arthur, J., & Longoria, N. (1995). *Living in Family Environments (LIFE) coding system: Reference manual for coders*. Oregon Research Institute.

Houben, M., Van Den Noortgate, W., & Kuppens, P. (2015). The relation between short-term emotion dynamics and psychological well-being: A meta-analysis. *Psychological Bulletin, 141*(4), 901–930. https://doi.org/10.1037/a0038822

Kalokerinos, E. K., Murphy, S. C., Koval, P., Bailen, N. H., Crombez, G., Hollenstein, T., et al. (2020). Neuroticism may not reflect emotional variability. *Proceedings of the National Academy of Sciences, 117*(17), 9270–9276. https://doi.org/10.1073/pnas.1919934117

Kashdan, T. B., & Rottenberg, J. (2010). Psychological flexibility as a fundamental aspect of health. *Clinical Psychology Review, 30*(7), 865–878. https://doi.org/10.1016/j.cpr.2010.03.001

Kashdan, T. B., Uswatte, G., Steger, M. F., & Julian, T. (2006). Fragile self-esteem and affective instability in posttraumatic stress disorder. *Behaviour Research and Therapy, 44*(11), 1609–1619. https://doi.org/10.1016/j.brat.2005.12.003

Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010). Emotional inertia and psychological maladjustment. *Psychological Science, 21*(7), 984–991. https://doi.org/10.1177/0956797610372634

Kuppens, P., Sheeber, L. B., Yap, M. B., Whittle, S., Simmons, J. G., & Allen, N. B. (2012). Emotional inertia prospectively predicts the onset of depressive disorder in adolescence. *Emotion, 12*(2), 283–289. https://doi.org/10.1037/a0025046

Larson, R., & Csikszentmihalyi, M. (1983). The experience sampling method. In H. T. Reis (Ed.), *Naturalistic approaches to studying social interactions: New directions for methodology of social and behavioral science* (pp. 41–55). Jossey-Bass.

Lavelli, M., & Fogel, A. (2013). Interdyad differences in early mother–infant face-to-face communication: Real-time dynamics and developmental pathways. *Developmental Psychology, 49*(12), 2257–2271. https://doi.org/10.1037/a0032268

Lewis, M. D. (2000). Emotional self-organization at three time scales. In M. D. Lewis & I. Granic (Eds.), *Emotion, development, and self-organization: Dynamic systems approaches to emotional development* (pp. 37–69). Cambridge University Press. https://doi.org/10.1017/CBO9780511527883.004

Lewis, M. D. (2011). Dynamic systems approaches: Cool enough? Hot enough? *Child Development Perspectives, 5*(4), 279–285. https://doi.org/10.1111/j.1750-8606.2011.00190.x

Lougheed, J. P. (2020). Parent-adolescent dyads as temporal interpersonal emotion systems. *Journal of Research on Adolescence, 30*(1), 26–40. https://doi.org/10.1111/jora.12526

Lougheed, J. P., Benson, L., Cole, P. M., & Ram, N. (2019). Multilevel survival analysis: Studying the timing of children's recurring behaviors. *Developmental Psychology, 55*(1), 53–65. https://doi.org/10.1037/dev0000619

Lougheed, J. P., Brinberg, M., Ram, N., & Hollenstein, T. (2020). Emotion socialization as a dynamic process across emotion contexts. *Developmental Psychology, 56*(3), 553–565. https://doi.org/10.1037/dev0000801

Lougheed, J. P., & Hollenstein, T. (2014). *Specific affect coding system manual: 5-code version*. Unpublished manual.

Lougheed, J. P., & Hollenstein, T. (2016). Socioemotional flexibility in mother-daughter dyads: Riding the emotional rollercoaster across positive and negative contexts. *Emotion, 16*(5), 620–633. https://doi.org/10.1037/emo0000155

Lougheed, J. P., & Hollenstein, T. (2018). Methodological approaches to studying interpersonal emotion dynamics. In A. K. Randall & D. Schoebi (Eds.), *Interpersonal emotion dynamics in personal relationships* (pp. 75–92). Cambridge University Press.

Miller, J. D., & Pilkonis, P. A. (2006). Neuroticism and affective instability: The same or different? *American Journal of Psychiatry, 163*(5), 839–845.

Patterson, G. R. (2016). *Coercion theory: The study of change. The Oxford handbook of coercive relationship dynamics* (pp. 7–22). Oxford University Press.

Pfaltz, M. C., Michael, T., Grossman, P., Margraf, J., & Wilhelm, F. H. (2010). Instability of physical anxiety symptoms in daily life of patients with panic disorder and patients with posttraumatic stress disorder. *Journal of Anxiety Disorders, 24*(7), 792–798. https://doi.org/10.1016/j.janxdis.2010.06.001

Schiepek, G., Aichhorn, W., Gruber, M., Strunk, G., Bachler, E., & Aas, B. (2016). Real-time monitoring of psychotherapeutic processes: Concept and compliance. *Frontiers in Psychology, 7*, 604. https://doi.org/10.3389/fpsyg.2016.00604

Slepian, M. L., Bogart, K. R., & Ambady, N. (2014). Thin-slice judgments in the clinical context. *Annual Review of Clinical Psychology, 10*, 131–153. https://doi.org/10.1146/annurev-clinpsy-090413-123522

Snyder, J., & Stoolmiller, M. (2002). Reinforcement and coercion mechanisms in the development of antisocial behavior: The family. In J. B. Reid, G. R. Patterson, & J. Snyder (Eds.), *Antisocial behavior in children and adolescents: A developmental analysis and model for intervention* (pp. 65–100). American Psychological Association. https://doi.org/10.1037/10468-000

Snyder, J., Stoolmiller, M., Wilson, M., & Yamamoto, M. (2003). Child anger regulation, parental responses to children's anger displays, and early child antisocial behavior. *Social Development, 12*(3), 335–360. https://doi.org/10.1111/1467-9507.00237

Thompson, R. J., Berenbaum, H., & Bredemeier, K. (2011). Cross-sectional and longitudinal relations between affective instability and depression. *Journal of Affective Disorders, 130*, 53–59. https://doi.org/10.1016/j.jad.2010.09.021

Twivy, E., Grol, M., & Fox, E. (2020). Individual differences in affective flexibility predict future anxiety and worry. *Cognition and Emotion*, 1–10. https://doi.org/10.1080/02699931.2020.1843407 van der Giessen, D., & Bögels, S. M. (2018). Father-child and mother-child interactions with children with anxiety disorders: Emotional expressivity and flexibility of dyads. *Journal of Abnormal Child Psychology, 46*(2), 331–342. https://doi.org/10.1007/s10802-017-0271-z

van der Giessen, D., Hollenstein, T., Hale, W. W., Koot, H. M., Meeus, W., & Branje, S. (2015). Emotional variability in mother-adolescent conflict interactions and internalizing problems of mothers and adolescents: Dyadic and individual processes. *Journal of Abnormal Child Psychology, 43*(2), 339–353. https://doi.org/10.1007/s10802-014-9910-9

Wass, S. V., Smith, C. G., Clackson, K., & Mirza, F. U. (2020). In infancy, it's the extremes of arousal that are 'sticky': Naturalistic data challenge purely homeostatic approaches to studying self-regulation. *Developmental Science*, e13059. https://doi.org/10.1111/desc.13059

Witherington, D. C., & Boom, J. (2019). Conceptualizing the dynamics of development in the 21st century: Process, (inter) action, and complexity. *Human Development, 63*(3–4), 147–152.

Yang, X., Ram, N., Lougheed, J. P., Molenaar, P., & Hollenstein, T. (2019). Adolescents' emotion system dynamics: Network-based analysis of physiological and emotional experience. *Developmental Psychology, 55*(9), 1982–1993. https://doi.org/10.1037/dev0000690

Chapter 7
On the Signal-to-Noise Ratio in Real-Life Emotional Time Series

Egon Dejonckheere and Merijn Mestdagh

Abstract How emotions unfold in everyday life, naturally interact with each other over time, change in function of different real-life situations or contexts, and how these dynamic patterns relate to person-level characteristics are areas of investigation that are gaining increased interest among emotion researchers. At the same time, however, there is also growing awareness that adequately assessing affect dynamics 'in the wild' may be harder than previously anticipated. A central predicament is that the data quality of current daily life studies is often insufficient to pick up on meaningful regularities in real-life emotion time series, concealing the true dynamical features of people's affective life. In this chapter, we introduce the signal-to-noise ratio (SNR) as a measure of data quality, designed to disentangle the power of people's latent emotional signal from inevitable background noise. Breaking down the SNR into its different constituents, we lay out an overarching framework with various methodological strategies to improve the SNR of real-life affective time series, with the ultimate goal to reliably evaluate the internal and external validity of ecological dynamics of affect. Providing preliminary empirical evidence, we hope that future daily life studies will implement our suggestions, to truly behold the dynamical nature of everyday emotion.

Keywords Affect dynamics · Signal-to-noise ratio · Measurement error · Innovation · Context · Auto-correlation · Measurement burst · Inertia

7.1 Introduction

Investigating how affective states wax and wane in the realm of everyday life is an essential complement to studying emotional responding in standardized, yet often artificial, lab settings. Unparalleled in their ecological validity, daily life methods

E. Dejonckheere (✉) · M. Mestdagh
Faculty of Psychology and Educational Sciences, Leuven, Belgium
e-mail: egon.dejonckheere@kuleuven.be; merijn.mestdagh@kuleuven.be

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_7

such as experience sampling (ESM) provide researchers with a unique first-seat insight into the authentic structure and natural dynamical regularities of people's emotional life. Within individuals, for example, ESM researchers may show interest in the circadian rhythms of emotion (e.g., Murray et al., 2009), the ability of an emotional state to predict its future trajectory (e.g., emotional inertia, Cole & Hollenstein, 2018), the concurrent and temporal interplay between various emotions (e.g., the relation between positive [PA] and negative affect [NA], Dejonckheere et al., 2018; emotional augmentation and blunting, Pe & Kuppens, 2012), and natural emotional change as a function of different internal and external processes or stimuli (e.g., emotion regulation, Kalokerinos et al., 2017; encountering negative events, Koval et al., 2015). In turn, between individuals, ESM studies may investigate how these dynamical patterns of emotion are informative for various person-level features or characteristics, such as psychological well-being or maladjustment (e.g., Houben et al., 2015), personality traits (e.g., Bringmann et al., 2016) or emotional intelligence (e.g., Robinson et al., 2020).

Although each of these studies typically require a unique and tailored ESM protocol to validly answer their research questions, a common prerequisite for all their designs is that they accurately describe the real-life patterns of people's emotional life. If ESM time series do not reliably represent the natural ebbs and flows of participants' affective experiences, emotion researchers run the risk of drawing erroneous conclusions about emotions' true dynamic properties, their causes and consequences (i.e., together referred to as the *internal* validity of affect dynamics), but also how differences in these temporal trajectories of emotion may explain individual variation in important person-level variables (i.e., the *external* validity of affect dynamics).

Today, there is growing consensus that an accurate evaluation of the internal and external validity of real-life affect dynamics may be harder than previously thought. Regarding the internal validity, for example, recent research shows that trying to determine a person's current emotional state is less effective when relying on rather complex dynamical models of affect compared to the simplified version of these models (Bulteel et al., 2018). This is remarkable, because more complex models allow ESM researchers to incorporate multiple streams of information (e.g., personal or contextual data), and are therefore thought to be a closer approximation of reality. In contrast, the very basic models merely rely on a person's previous emotions to determine his or her current emotional state, disregarding other potentially useful sources of information relevant for the conception of an emotional response (e.g., Frijda, 1988). Nevertheless, these simple affect dynamic models outperform the complex ones in terms of predictive accuracy (Bulteel et al., 2018), raising the question whether there may be methodological issues associated with ESM that currently conceal the complex (yet true) dynamical features of people's affective life.

Second, also the external validity of affect dynamics was recently questioned in various psychological domains. From common symptom types in mental health research (Dejonckheere et al., 2019a), to the big five traits in the study of personality (Hisler et al., 2020; Kalokerinos et al., 2020; Wendt et al., 2020), to multiple facets of emotional intelligence (MacCann et al., 2020), recent research shows that more complex metrics of affect dynamics no longer explain individual differences in these person-level outcomes once the predictive power of simple mean levels of PA and NA is taken into account. Again, the observation that the dynamical regularities of people's emotional life play a negligible role in our understanding of their well-being, personality or emotional intelligence seems to be counter-intuitive and contests both the existing theories and intuitive beliefs we hold about emotion: Could there be issues with the reliability of ESM emotion time series that obscure a meaningful relation?

Because these issues with the internal and external validity of affect dynamics will be an important concern for next-generation ESM research to address (e.g., Wendt et al., 2020), this chapter provides an overview of different methodological strategies to increase the data quality of emotion time series. Essentially, each strategy fits in an overarching framework that has the ultimate goal to increase the signal-to-noise ratio (SNR) of the emotional time series ESM researchers investigate, and combining multiple strategies in your future ESM protocol will likely be most effective to reliably evaluate the internal and external validity of real-life affect dynamics (Dejonckheere et al., 2020).[1]

7.2 What Is the Signal-to-Noise Ratio of a Time Series?

While the SNR is an established metric in many other time series disciplines (e.g., audiology, Shojaei et al., 2016; biochemistry, Beal, 2015; econometrics, Saothayanun & Thangjai, 2018), it is a relatively unknown concept in the study of psychology. Although the operationalization and substantive interpretation may slightly vary across disciplines, the SNR can be easily applied to psychological time series data as well.

At its core, the SNR can be understood as a measure of data quality (Yu et al., 2018). As the name gives away, the SNR compares the power of desired signal to the power of background noise generated by a system (e.g., fMRI scanners, ecosystems, stock markets, etc.; Welvaert & Rosseel, 2013):

$$SNR = \frac{power\ signal}{power\ noise} \tag{7.1}$$

Broadly defined, the *signal* concerns the stream of meaningful information the system produces, while *background noise* refers to random (i.e., unpredictable) environmental interferences that distort that signal. As Eq. (7.1) illustrates, higher SNR values indicate higher data quality. Specifically, ratios higher than 1 imply that

---

[1] In this book chapter, we elaborate on some of the ideas formulated in our response *Reply to: Context matters for affective* chronometry (Dejonckheere et al., 2020) to Lapate and Heller's (2020) commentary on our original article (Dejonckheere et al., 2019a). Because this chapter constitutes a conceptual extension of our reply, some theoretical overlap is inevitable.

the power of a system's signal effectively outweighs the power of background noise, and that meaningful information can be detected. In contrast, SNRs smaller than 1 indicate that the power of a system's signal is exceedingly overruled by the power of random environmental influences, making it very hard to recover meaningful system information.

In the psychology of affect, researchers consider *emotional* systems (e.g., human beings responding to their natural environment; Loossens et al., 2020). Here too, the observed affective time series of ESM participants can be decomposed into a signal and noise term (Dejonckheere et al., 2020). A common and popular way to statistically operationalize the power of people's true emotional signal is to define it as the variance of a latent auto-regressive (AR) model of order 1 [i.e., an AR(1) model] (Schuurman et al., 2015; Schuurman & Hamaker, 2019):

$$\textit{power signal} = \mathrm{Var}\left(\tilde{NA}_t = a\,\tilde{NA}_{t-1} + \varepsilon_t \right) \tag{7.2}$$

As can be seen from Eq. (7.2), an individual's true or latent (negative) affective signal $\widetilde{NA}$ is defined by two terms. First, it is determined by a person-specific AR parameter (a) that captures the degree with which an individual's current latent affective state (e.g., a participant's true level of momentary $\tilde{NA}$ assessed at time point t) can be predicted from his or her previous latent affective state (e.g., a participant's true level of momentary $\tilde{NA}$ assessed at time point $t - 1$). In dynamical system terms, this part of the equation refers to a person's *attractor strength* (Kuppens et al., 2010b), and reflects the speed with which an individual generally returns to his or her emotional baseline or homebase after responding to a stimulus that is of personal relevance (with higher a indicating slower return; Chow et al., 2005). Indeed, people's emotional reactions do not unfold in a vacuum, but are embedded in a larger context of personally relevant stimuli and events they respond to (Frijda, 1988). The collection of these contextual stimuli is situation-specific (i.e., different for each t), and cannot be captured by the person-specific AR parameter. They are therefore represented by a second term ε_t, generally referred to as *innovation* or *dynamic noise* (Schuurman et al., 2015). This dynamic noise term roughly corresponds to the intensity of the emotional stimulus a person reacts to at time point t, and carries over to next time points via the person-specific AR relation (hence the name *dynamic* noise; Schuurman & Hamaker, 2019).

Unfortunately, we are unable to directly observe people's true emotional signal. There is a degree of measurement error (ω) associated with each emotional assessment t that conceals participants' true momentary affective response. These random and unpredictable distortions are caused by moment-specific biases such as, for example, inattention, reactivity and fatigue (e.g., Fuller-Tyszkiewicz et al., 2013). Compared to innovation or dynamic noise, these interferences are restricted to each particular emotional assessment, and therefore do not resonate to subsequent assessments (Schuurman et al., 2015; Schuurman & Hamaker, 2019). The variance in measurement error across all momentary assessments represents the power of *measurement noise*:

$$power\,noise = \mathrm{Var}\left(\omega_t\right) \tag{7.3}$$

In sum, the combination of Eqs. (7.2) and (7.3) illustrates that participants' observed level of momentary (e.g., negative) affect can be understood as:

$$NA_t = a\,\tilde{NA}_{t-1} + \varepsilon_t + \omega_t \tag{7.4}$$

Accordingly, we can define the SNR of an affective time series as:

$$SNR = \frac{\mathrm{Var}\left(\tilde{NA}_t = a\,\tilde{NA}_{t-1} + \varepsilon_t\right)}{\mathrm{Var}\left(\omega_t\right)} \tag{7.5}$$

7.3 Determinants of the Signal-to-Noise Ratio

Equation (7.5) explains us how we can impact, and ultimately maximize the SNR of the affective time series we investigate. After all, attempts to advance the SNR lead to better data quality in ESM (Yu et al., 2018), promoting a more reliable evaluation of the internal and external validity of real-life affect dynamics.

But how troublesome is the SNR situation in contemporary ESM research really? To get an indication, we reanalyzed 15 prototypical ESM studies reported in Dejonckheere et al. (2019a), and computed the SNR for participants' PA and NA time series following Eq. (7.5) (see also Dejonckheere et al., 2020). As shown in Fig. 7.1, many of the datasets had median SNRs that barely exceeded the critical threshold of 1, which would indicate that 50% of the participants in that particular ESM study presented affective time series in which the level of estimated measurement noise overruled the power of their latent emotional signal. For the total sample in our meta-analysis (n = 1777), 30% of the subjects had an emotional SNR smaller than 1 for PA, and 42% for NA. Although each individual ESM study was carried out to answer a different research question, and their protocols, affect items and sample characteristics are therefore unique in design, these numbers suggest that the quality of current ESM time series is below par. This could explain why real-life affect dynamics have poor internal and external validity (e.g., Bulteel et al., 2018; Dejonckheere et al., 2020; Wendt et al., 2020): Current practices in ESM research prohibit the detection of meaningful dynamical regularities in emotion time series.

Then how may we boost the SNR of ESM time series? To guide the reader through the next sections, Fig. 7.2 presents a graphical overview of the different determinants that make up this metric (a, ε and ω), which researchers can impact to improve the SNR. For each determinant, we visualize two simulated affective time series that result in a low and high SNR (while the value of other determinants is

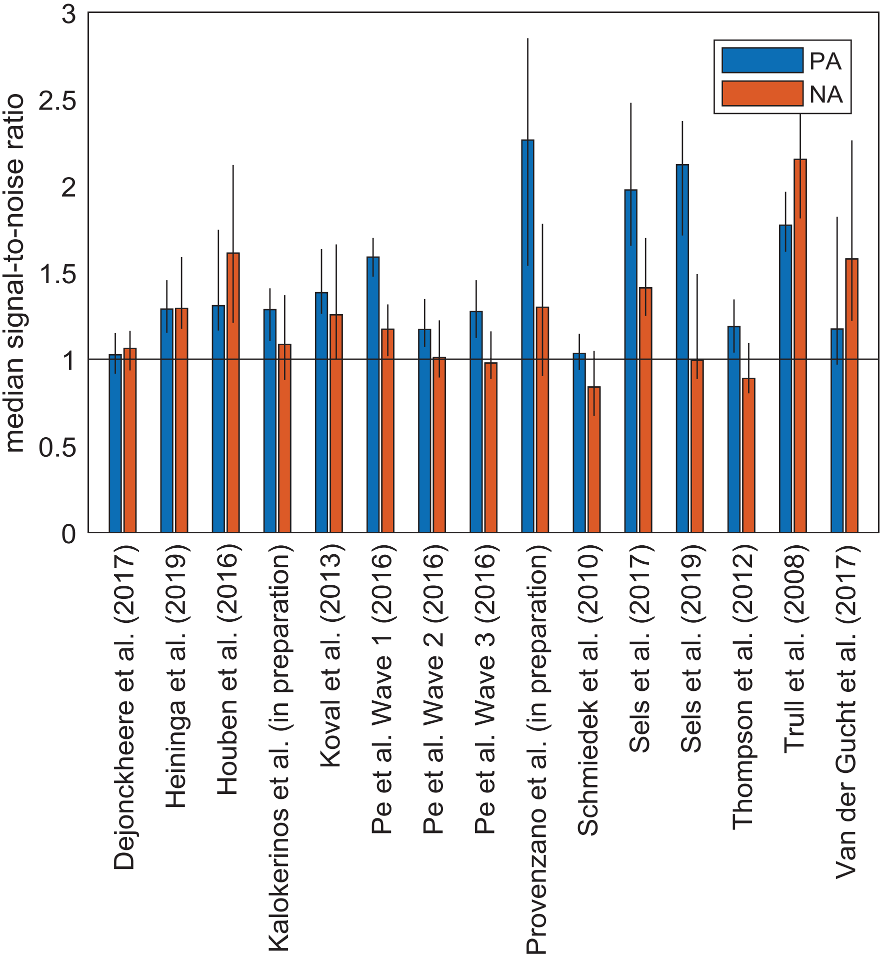


Fig. 7.1 Evaluating the SNR in conventional ESM research. The median SNR for PA (*blue bars*) and NA (*red bars*) for each of the 15 datasets reported in Dejonckheere et al. (2019a) ($n = 1777$), with the error bars indicating the 95% confidence interval (derived from 2000 bootstraps)

held constant). Metaphorically, you can think of the time series depicted in Fig. 7.2 as a pearl necklace: The string reflects a person's latent continuous emotional response ($\tilde{NA}$), while the beads represent a series of discrete affect ratings (NA_t). To increase the SNR of an emotional time series, researchers should pursue substantially pronounced emotional strings (ε), and place the individual beads in such a way that they closely mirror the participant's original emotional response (both in time [a] and in deviation [ω]). In the next paragraphs, we will discuss how this analogy translates into concrete guidelines for each determinant.

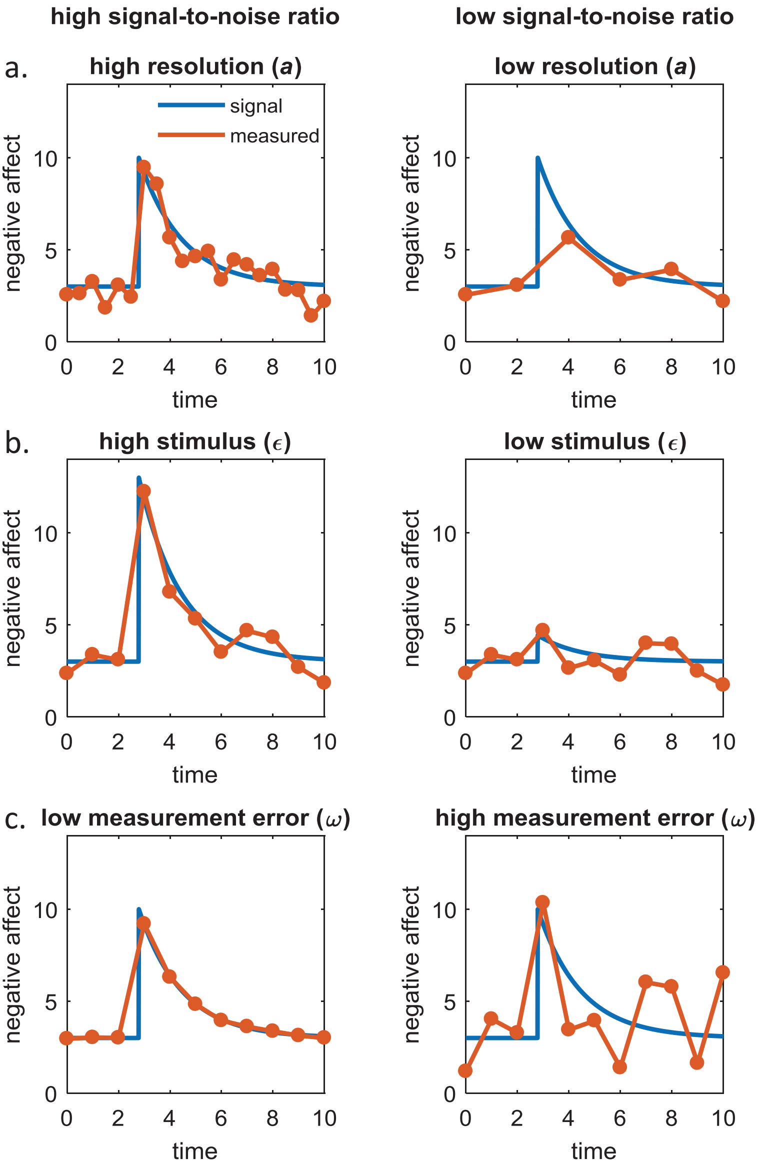


Fig. 7.2 Graphical representation of the various constituents (*a*, ε and ω) that make up the SNR. Hypothetical emotional trajectory of an individual who reacts to a negative contextual stimulus at time point 3. The *continuous blue line* represents that person's actual (latent) emotional response, while the *discrete red dots* depict his (observed) affective intensity ratings. The left and right columns refer to scenarios that exhibit a high and low SNR, respectively. (**a**) Manipulation of the temporal measurement resolution (short versus long time intervals). (**b**) Manipulation of the stimulus' emotional intensity (strong versus low emotional intensity). (**c**) Manipulation of the measurement noise associated with the affect ratings (assessments that are noise-free versus overwhelmed by measurement noise)

7.3.1 Recovering the Latent AR Parameter: Temporal Measurement Resolution

As mentioned earlier, the AR parameter a captures the degree with which a person's latent emotional reaction generally lingers after an affective stimulus was introduced (Kuppens et al., 2010a), and indicates how well we can predict its future (linear) trajectory (Headey & Wearing, 1989). When a is high, we describe a person's emotional recovery function as highly inert and resistant to the influence of internal regulatory processes (i.e., low attractor strength; see Fig. 7.3 panel A; Kuppens et al., 2010b). In contrast, when a is low, that person's emotional responding is highly susceptible to the system's regulatory forces, which will impact its original trajectory (i.e., high attractor strength; see Fig. 7.3 panel B).

Following this interpretation, a can be understood as a person-level indicator of the (linear) self-predictability of an affective state over time, and people's (observed) affective time series are known to vary in the amount of auto-regression they exhibit (Bos et al., 2019; Bulteel et al., 2018). Although a is considered person-specific, and we therefore cannot directly boost its magnitude to maximize the SNR, the upper limit of its estimation is determined by measurement practices (Dejonckheere et al., 2020). Specifically, because a refers to the temporal (un)predictability of a latent affective state (i.e., *How well can I predict a person's true emotion level at the next time point?*), the relative size of this parameter will naturally depend on the temporal assessment resolution that was used during the study protocol (see Fig. 7.2 panel A): Larger time intervals between consecutive measurement occasions t–1 and t will diminish the predictive accuracy of future affective states, and typically result in lower AR parameters (Bulteel et al., 2018). For example, making the average time interval between two consecutive measurement twice as long will reduce the estimated AR parameter by a power of 2 (e.g., from .40 to .16).

Intuitively, this makes sense, as the lingering effect of an emotional response generally diminishes as time after the instigating stimulus elapses (Anderson & Adolphs, 2014; Hemenover, 2003). As such, a measurement protocol in which successive measurements are simply too far apart will not be able to adequately capture the meaningful recovery of a person's emotional system, because full recovery likely took place in between measurement occasions (e.g., Schiepek et al., 2016). In other words, as a guiding principle, it is crucial that the temporal spacing between consecutive measurements is smaller than the rate of change of the emotions under study (Boker et al., 2009). When researchers assess emotional change with a higher temporal resolution, the serial dependency between consecutive emotional assessments increases (Ram et al., 2017), which allows for more fine-grained distinctions between individuals in terms of their personal AR parameter.

To illustrate the impact of a study's adopted assessment resolution on the recovery of participants' individual AR parameter, Fig. 7.4 visualizes three empirical ESM protocols from previous research that significantly differ in the average time interval between their emotional assessments (i.e., 1 day versus 104 min versus 13 min, respectively). For each protocol, we present the distribution of personal AR

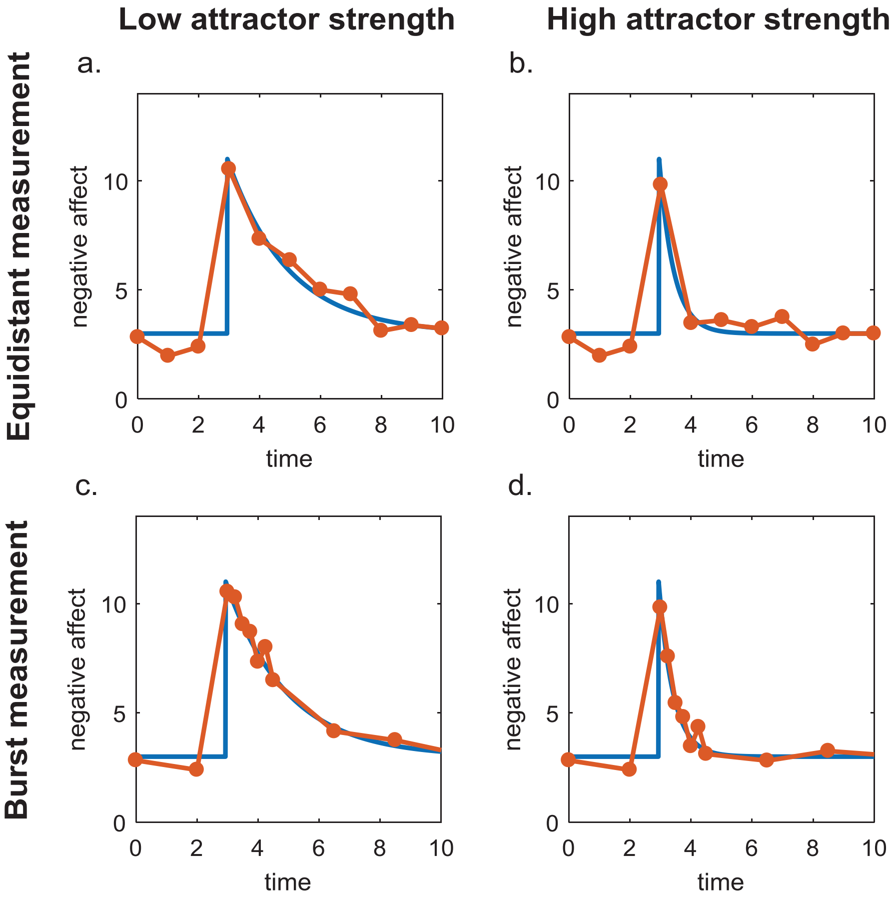


Fig. 7.3 Comparing the AR estimation in an equidistant measurement protocol versus micro-level measurement burst design. Simulated emotion time series for different hypothetical participants who react to a negative contextual stimulus at time point 3. The *continuous blue lines* represent their actual (latent) emotional response, while the *discrete red dots* depict their (observed) affective intensity ratings. (**a**) Participant who exhibits low attractor strength in an equidistant measurement protocol, which is adequately captured by the AR estimation. (**b**) Participant who exhibits high attractor strength in an equidistant measurement protocol, which is poorly captured by the AR estimation. (**c**) Participant who exhibits low attractor strength in a micro-level measurement burst design, which is adequately captured by the AR estimation. (**d**) Participant who exhibits high attractor strength in a micro-level measurement burst design, which is adequately captured by the AR estimation

parameters for PA, alongside the corresponding boxplot. Although a direct comparison between protocols is difficult due to other study-specific characteristics (e.g., total study duration, number of items per assessment, unique participant features, etc.), the boxplots suggest that longer time windows result in lower emotional AR estimations. Moreover, when longer time intervals between assessments exist, the proportion of participants that shows an AR parameter that does not significantly

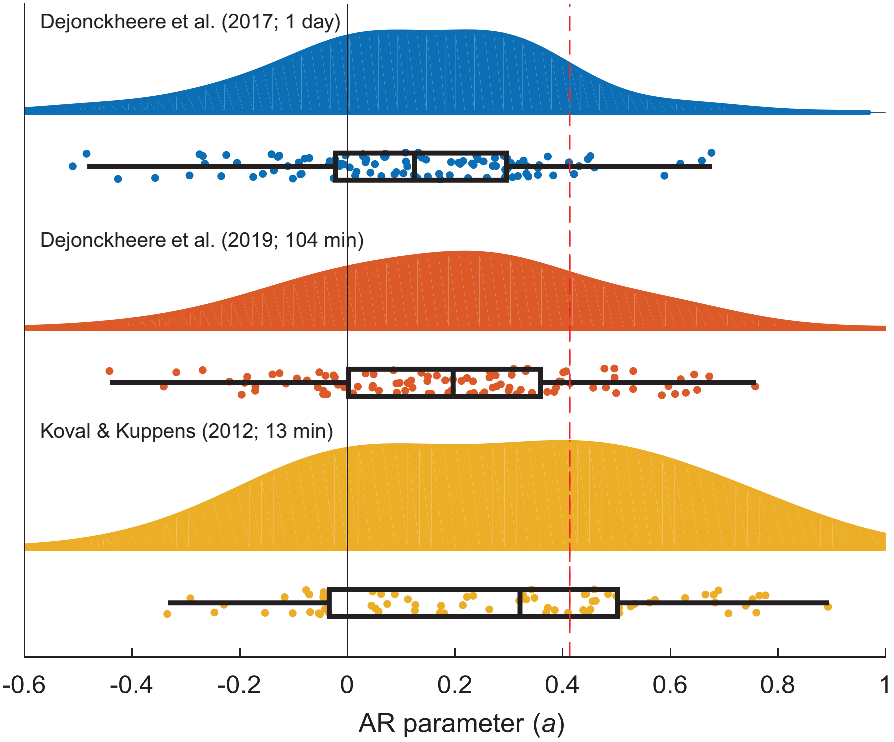


Fig. 7.4 Evaluating the role of temporal assessment resolution on the estimation of people's AR parameter. For each dataset, the raincloud plot visualizes the distribution of participants' personal auto-regressive effects in PA (i.e., the mean of emotion items *relaxed* and *happy*). The average time interval between two measurement occasions is presented between brackets. To maximize a fair comparison between studies, we only selected the first 30 affect ratings for each participant to estimate *a*. The *red dashed line* indicates the corresponding significance threshold

differ from zero increases (for an estimation based on 30 time points; i.e., 90, 82, and 62%, respectively). Conceptually, a non-significant AR parameter seems counter-intuitive, as it suggests that the momentary affect ratings of such an individual are completely instantaneously determined, and no carry-over effect in the form of emotional recovery between assessments takes place (i.e., there is no *emotional* inertia). Because such a motion is highly unlikely in real life, we assume that the temporal resolution of the assessment protocol was simply too low to adequately capture these individuals' emotional recovery.

But how do we determine the appropriate time scale with which emotions should be assessed? Ideally, a scenario in which we continuously monitor changes in an affective state (i.e., where the interval between *t*–1 and *t* is virtually zero) would enable the most accurate AR estimation. Following our necklace metaphor, this would imply that ESM researchers drastically increase the number of individual beads, in order to adequately reconstruct participants' underlying emotional recovery function. However, to date, we can only access changes in experiential phenomena via repeated discrete self-reports, which is inherently intrusive and burdensome for participants (Schimmack, 2003; Stone et al., 2003). As such, these constraints preclude an endless expansion of the assessment frequency adopted in an ESM protocol.

Alternatively, instead of focusing on the appropriate *number* of assessments, ESM researchers should be equally concerned with the *timing* of these assessments (i.e., the exact temporal location of the different discrete beads to recover people's latent emotional signal; Kuiper & Ryan, 2018). That is, although inflating the number of discrete measurement occasions will result in shorter time intervals between occasions (when the study duration is held constant), chances still exist these assessments largely fail to accurately describe people's emotional recovery function when they are prompted at wrong moments (e.g., Fig. 7.3 panel B). Instead of holding on to measurement intervals that are more or less equidistant in time (which is common practice in contemporary ESM research), a more tailored ESM protocol that temporarily amplifies the rate of affective assessments when participants significantly deviate from their affective homebase, may enable a more accurate evaluation of their personal AR parameter (e.g., Schiepek et al., 2016). The flexible interval width of this *micro-level measurement burst design* (e.g., Stawski et al., 2015) softens the natural trade-off between increasing sample frequency and participant burden: Researchers may adequately assess participants' emotional recovery function while the total number of to be completed assessments should not be drastically increased (e.g., compare upper versus lower panels in Fig. 7.3). Although this approach may enable a better AR estimation, possible impediments to this type of measurement design include the implementation of online computational models in ESM software to determine whether participants are out of their personal affective equilibrium, the acquaintance with statistical models that do not require equally spaced time points (e.g., continuous-time Ornstein-Uhlenbeck models; Oravecz et al., 2009), and variable study durations across participants (when total number of assessments is held constant) that could lead to differences in the ecological validity of people's affective time series.

7.3.2 Maximizing the Event-Specific Noise Term: Strong Contextual Stimuli

Innovation or dynamical noise ε refers to the variance in a person's affective responding that cannot be explained by the latent AR model (Schuurman et al., 2015). Consequently, this error term is thought to capture change in people's emotional trajectory that does not stem from endogenous feedback processes (i.e., the person-specific AR parameter), but from the various contextual stimuli people encounter and react to in their environment. Although this noise term ε is serially uncorrelated and specific for each t, it may shape the value of subsequent latent emotional states via the AR relation (Dejonckheere et al., 2020). As such, this situation-specific error term ε more or less refers to the (subjective) emotional intensity of the stimuli that people process.[2] For example, the sudden suffering of a goal of one's favorite soccer team will trigger an emotional reaction that cannot be accurately predicted from a person's previous emotional state (because it is unexpected), but it will have its effect on subsequent emotional assessments (in the form of emotional recovery).

In line with our necklace analogy, ε reflects the shape of people's underlying emotional string (i.e., explosive versus flat). Strong affect-laden stimuli, situations or events evoke strong emotional reactions, and increase the likelihood that people are temporarily thrusted out of their affective homebase (Chow et al., 2005). In turn, the emotional recovery process will be sizeable, which evidently produces a more pronounced emotional signal (see Fig. 7.2 panel B). The more pronounced this emotional signal, the easier it is to detect, as it effectively overrides the inevitable background noise associated with measurement practices. As such, exposing participants to events or situations that elicit strong emotional reactions may offer new opportunities to increase the SNR of the respective emotional ESM time series (Dejonckheere et al., 2020; Lapate & Heller, 2020).

At first sight, it may feel counter-intuitive that ESM researchers would want to control the contextual input their participants receive. After all, this data collection method is recognized for its ecological validity (Myin-Germeys et al., 2018; Trull & Ebner-Priemer, 2009), and is used to understand how emotions naturally come and go in the realm of ordinary life without any top-down interventions. This is in stark contrast with traditional lab research, where researchers experimentally induce isolated emotional states under controlled and standardized circumstances, and therefore have perfect insight in the causes and consequences of an emotional response. Because of the intrinsic tension between ecological validity and standardization, a downside to ESM (compared to experimental studies) is that real-life affect ratings are often equivocal, determined by a complex synergy of multiple ill-defined stimuli (Dejonckheere et al., 2019a). Not only are ESM researchers relatively clueless about the exact emotion-eliciting stimuli that shape participants' affective responses, the situations and events people experience on a daily basis are often emotionally unprovocative and short-lived (Dejonckheere et al., 2020). Bypassing these inherent limitations of ESM to get a closer indication of the contextual input participants receive, without carelessly undermining the ecological validity of this method, may boost the emotional signal value found in ESM time series.

To counter the fact that emotion ratings in daily life are often multi-determined, and that it is therefore challenging to isolate their direct cause, anchoring affective

---

[2] Some frameworks in the affect dynamics literature (e.g., Loossens et al., 2020) additionally break down ε_t into an innovation part (that captures deterministic contextual input) and a stochastic part (that captures built-in system noise). A more detailed discussion of this subdivision is beyond the scope of this chapter, but it explains the fractional translation of ε into the (perceived) emotional intensity of a stimulus.

assessments to specific events or stimuli could be worthwhile. In anchored ESM protocols, researchers track emotional change in daily life in relation to particular incidents or affairs. Instead of global momentary emotional assessments (e.g., *How sad do you feel right now?*), participants are instructed to rate their momentary emotion levels with regard to a specific and well-defined stimulus (e.g., *How sad do you feel right now, regarding your* [*partner, back pain, pregnancy, exams, job, etc.*]?). The selection of relevant stimuli may be fixed and determined a priori when researchers have a specific research question in mind (e.g., How do different emotions in the context of recent parenthood unfold?: *How* [*stressed, happy, etc.*] *are you about your new-born right now?*) or could be introduced bottom-up in the moment by the participants themselves. Here, participants first report on the event or stimulus that is currently most emotionally relevant via an open-ended question (e.g., *Describe the event or affair that triggers your current emotions.*). Next, via follow-up assessments, the natural emotional recovery with respect to the articulated event is evaluated, and new momentary relevant stimuli are disclosed that will serve as an input for subsequent affective assessments. Although this design would allow ESM researchers to delineate ecological emotional responses in relation to isolated stimuli, the possibility to assign conditional dependencies across measurements (where participants' responses at time t serve as input for their evaluations at time $t + 1$, $t + 2$, etc.) is currently lacking in many contemporary ESM applications. Furthermore, it remains to be investigated to what extent people are truly able to detach their emotional evaluation related to a single stimulus from their global affective state (e.g., carry-over effects between stimuli, Schmidt & Schmidt, 2016), and if these type of assessments do not induce stronger emotional reactivity (e.g., Schwarz, 1999).

Anchoring emotional assessments in ESM does not tackle the problem that the events and situations people encounter on a regular basis may not be very emotionally moving (i.e., their emotional string is not very pronounced). Moreover, because individuals act in their own personal ecology, the contextual input they receive may differ in numerous ways (Kahneman et al., 2004), which hampers a direct comparison of their affective time series. Here, quasi-experimental ESM studies, in which researchers track natural emotional change around a standardized and impactful stressor could be promising (Dejonckheere et al., 2020). Researchers may introduce that stressor into the daily lives of their participants top-down (e.g., a Trier Social Stress Task; Koval & Kuppens, 2012), or they may anticipate the occurrence of a real-life event to design a study around (e.g., the release of exam results, Dejonckheere et al., 2019b; Kalokerinos et al., 2019; Metalsky et al., 1993; the implementation of COVID-19 lockdown measures, Dejonckheere et al., 2021; Taquet et al., 2020; the onset of a depressive episode, Wichers et al., 2016; the death of a beloved one, Folkman, 1997). In both cases, all subjects are exposed to the same compelling stimulus, which allows a more controlled comparison of their emotional trajectory, but real-life stressors have the strength that they are unparalleled in their ecological quality. However, a possible downside to these naturalistic stimuli is that they are sometimes relatively difficult to predict prospectively, which may result in longer study durations (e.g., Folkman, 1997) or smaller sample sizes (e.g., Dejonckheere et al., 2021; Wichers et al., 2016). Nevertheless, this quasi-experimental approach can reconcile both the naturalistic qualities of ESM and the more standardized setting of lab experiments (Dejonckheere et al., 2019b).

7.3.3 Reducing Momentary Measurement Noise: Assessing Measurement Error

Finally, ESM researchers can also improve the SNR of an affective time series by diminishing the measurement error ω that is associated with their assessment procedures (see Fig. 7.2 panel C). Attempts to reduce the incidental distortions inherent to people's momentary affect ratings may produce a closer approximation of their true emotional response, and therefore minimize the bias present in their AR parameter estimation (e.g., Staudenmayer & Buonaccorsi, 2005). Thus, in line with our necklace metaphor, ω indicates the extent with which the individual beads properly link up with the underlying string, indicating how much the discrete affect ratings deviate from a person's latent emotional signal.

Although the ubiquity of measurement noise in affective time series is commonly accepted among ESM researchers, this issue is largely ignored in the affect dynamics literature (e.g., Schuurman et al., 2015; Schuurman & Hamaker, 2019). Not only do emotion researchers often calculate affect dynamic measures from observed affect intensity scores (Dejonckheere et al., 2019a; Wendt et al., 2020), in an attempt to minimize participant burden or annoyance, they are generally reluctant to include exact repetitions of an item within the same momentary questionnaire (Schimmack, 2003). Singular items, however, prohibit an explicit momentary reliability assessment, leaving researchers in the dark about the exact amount of measurement error present in people's affect ratings. Instead of indirectly evaluating measurement noise via estimation procedures, future ESM designs could therefore benefit from randomly repeating (at least) one item at each measurement occasion, in order to get a direct indication of the measurement error associated with their protocol.

In a derivative effort to somehow mitigate the bias of measurement noise in affective time series, it is common practice in ESM research to average an *ad hoc* selection of specific same-valenced emotion items to construct a global positive or negative affective composite (Dejonckheere et al., 2019a). Combining individual emotion items into a single construct is thought to compensate for some of the measurement error associated with each individual rating (e.g., Nunnally, 1994), which may produce a higher SNR for the aggregated time series. To evaluate how this averaging procedure impacts the SNR, we compared the SNRs of each individual emotion item versus the two global PA and NA composites for a traditional ESM dataset (Sels et al., 2017). As shown in Fig. 7.5, the SNR for the two affective aggregates PA and NA is remarkably higher than for those of the same-valenced individual emotion items (except for *stressed*).

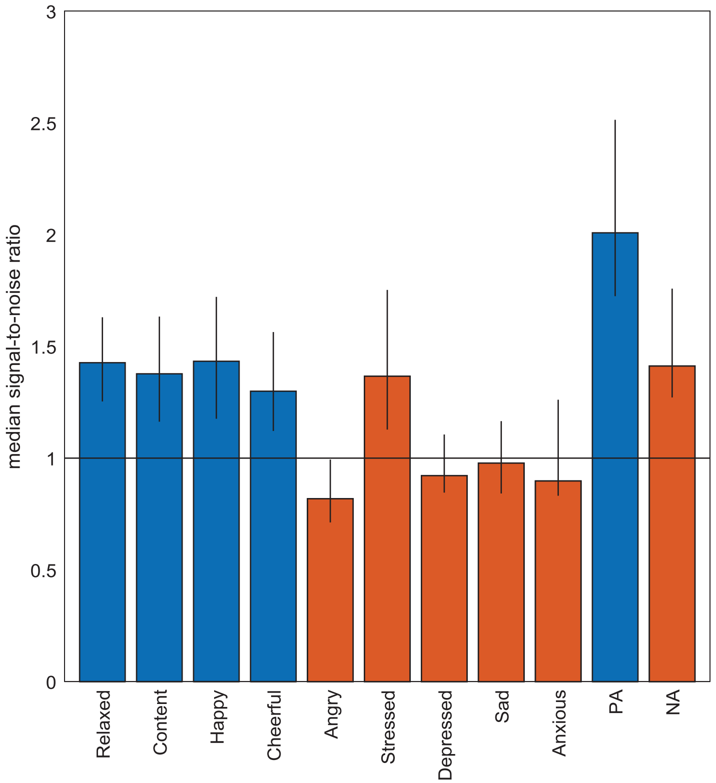


Fig. 7.5 Investigating the SNR of individual emotion items versus global PA and NA constructs in Sels et al. (2017). The median SNR for positive (*blue bars*) and negative (*red bars*) affect items or constructs, with the error bars indicating the 95% confidence interval (derived from 2000 bootstraps)

Nevertheless, when an emotional time series carries little signal, attempts to reduce measurement error will have little effect on the overall SNR. As such, procedures to reduce measurement noise are best used in combination with signal improvement strategies, because it is an illusion to believe researchers can entirely eliminate the measurement error associated with psychological self-report. Furthermore, it should be noted that the within-person internal consistencies of multi-item PA and NA constructs remain generally low (Dejonckheere et al., 2019a). This leaves the question to what extent the adopted discrete emotion items are truly interchangeable indicators of a global PA or NA composite, and what these averaged constructs really capture if their momentary reliabilities are so remarkably low. A more considerate and theory-driven selection of specific emotion-items could result in global PA and NA constructs that are both internally reliable and less sensitive to measurement error.

7.4 Combining Different Strategies to Improve the Signal-to-Noise Ratio

In this chapter, we introduced an overarching framework to promote the SNR of emotional time series in ESM research. Drawing from Eq. 7.5, this framework was structured around three key determinants that make up an emotional SNR. On the one hand, we discussed how researchers could seek to increase the power of participants' true emotional signal by fine-tuning AR estimations (a) or investigating more pronounced emotional reactions (ε). On the other hand, we advised researchers to evaluate and to reduce the measurement noise (ω) associated with their ESM protocol by creating reliable same-valenced affective composites instead of relying on singular emotion items. In the previous paragraphs, we explained how these general propositions translated into concrete design choices for each determinant individually (see Table 7.1 for an overview), but ideally ESM researchers may wish to apply these strategies to their protocol simultaneously, in order to optimize the quality of their time series data in the best possible way.

As a proof-of-concept that the combination of outlined strategies adds to an improved SNR, Panel A of Fig. 7.6 visualises how the median SNR of a real ESM study sample changes under different (artificial) strategy scenarios. In this ESM study (Dejonckheere et al., 2019b; Kalokerinos et al., 2019), we tracked the emotional trajectories of 101 first-year students around an impactful and personally relevant event, the release of their exam results. Students were instructed to rate both their unanchored momentary PA and NA (*Please indicate how positive/negative you are feeling right now?*), as well as multiple discrete emotion items anchored to their grades (*When you think about your grades right now, how* [*content, happy, proud, relieved, angry, anxious, ashamed, disappointed, stressed*] *are you feeling?*). Same-valenced emotion items were averaged at each measurement occasion to create an anchored PA and NA time series, and we computed an additional global anchored affective construct in which combined all items together (PA-NA). Finally, to simulate scenarios with different temporal resolutions, we relied both on participants' original time series, as well as a trimmed version in which we only considered every fifth emotional assessment.

Table 7.1 Summary of the proposed design strategies for each SNR determinant

SNR goal	Design strategy
Improve AR estimation (a)	– Increase temporal assessment resolution – Micro-level measurement burst design
Boost situational input (ε)	– Anchor emotional assessments to specific stimuli – Introduce/anticipate strong contextual events
Reduce measurement noise (ω)	– Explicitly assess measurement error via exact item repetitions – Reliably combine same-construct items

SNR Signal-to-noise ratio, *AR* Auto-regression

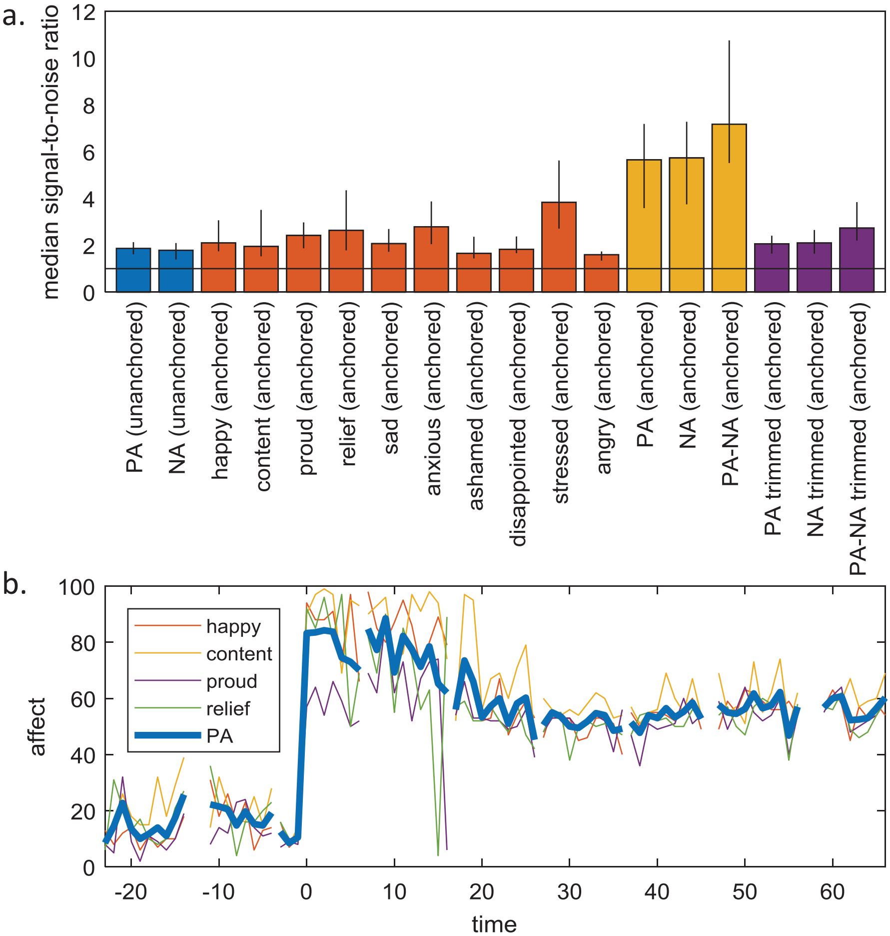


Fig. 7.6 Combining multiple strategies to improve the SNR in ESM time series. The results in both panels rely on data reported in Dejonckheere et al. (2019b) and Kalokerinos et al. (2019), in which we followed the emotional trajectories of 101 first-year students around the time they received their exam results. (**a**) The median SNR for different strategy scenarios, with the error bars indicating the 95% confidence interval (derived from 2000 bootstraps). (**b**) Real affective time series for an example participant with a high SNR (22.43). Time point zero indicates the first emotional assessment after the student consulted his or her exam results

As Panel A of Fig. 7.6 suggests, implementing multiple strategies in an ESM protocol at once markedly improves the SNR of emotion time series. First, for each scenario, the median SNR is almost around twice as high than those of most of the traditional ESM studies in Fig. 7.1, hinting at a positive impact of studying strong contextual stimuli on participants' emotional signal. Second, a comparison of the unanchored PA and NA items versus the anchored assessment of different discrete emotions shows that some (but not all) anchored emotion items bring about slight increases in the SNR (e.g., *stressed* but not *angry*). This suggests that assessing (some) emotional states in relation to a specific stimulus could potentially benefit the SNR. Third, averaging single anchored emotion items into an anchored global PA and NA composite drastically boosts the SNR, and its value increases even more when a global affective composite is considered (PA-NA). This indicates that the practice of averaging affect items reduces the measurement error associated with each individual emotion rating. Finally, when comparing the anchored PA and time series of the trimmed versus complete dataset, the SNR is considerably higher when a more fine-grained temporal assessment resolution is adopted. This suggests that an AR estimation is more accurate when the time interval between consecutive measurements is compressed.

But how does a high SNR visually manifest in an empirical ESM time series? Panel B of Fig. 7.6 depicts the PA time series for a participant with one of the highest SNRs in the study sample (SNR 22.43). First, the unexpected and sudden jump around the release of that participant's exam results indicates the introduction of a strong emotional stimulus, kicking that person out of emotional equilibrium and allowing emotional recovery to take place. Second, the aggregation of discrete emotion items into a global affective composite score clearly smooths the affective signal, eliminating some of the incidental and irregular drops and spikes that shape individual emotion ratings (which may be attributed to measurement error).

7.4.1 Interdependencies Among Design Strategies

Although the results in Fig. 7.6 suggest that implementing multiple design strategies positively amplifies the SNR, it is important to acknowledge that their effect is not necessarily additive. Similarly, the separate review for each individual SNR determinant does not imply that each design strategy independently impacts the SNR. As such, mutually comparing the effect of different design strategies is probably meaningless. There may be positive structural dependencies between the different strategies we discussed, making it difficult to disentangle their unique contribution in improving the SNR.

In contrast, it is equally possible that negative associations between particular design strategies exist, carrying an opposite impact on the SNR. That is, a proposed strategy to improve one SNR determinant may unintentionally compromise another one. For example, repeatedly exposing participants to micro-level measurement burst cycles has the goal to improve AR estimations, but could also induce increased annoyance with the protocol, resulting in more measurement error. Similarly, investigating real-life emotions in relation to a personally relevant and impactful event may boost the innovation parameter, but could equally introduce more missing data due to the study's increased interference with people's lives, impeding accurate AR estimations. As a final example, multiple items per construct may reduce the measurement error associated with each individual question, but result in longer momentary assessments, which is known to predict poor compliance (Eisele et al., 2020).

Depending on how all of these design choices relatively impact each determinant, SNR values may increase, decrease or remain unaltered. In either case, this uncertainty calls for future ESM studies that explicitly test how the SNR changes in function of various design alternatives.

7.4.2 Design Strategy Implementation Constraints

Finally, we realize that many of the outlined propositions may currently be difficult to implement, and that the resulting ESM protocols drastically differ from conventional ESM research practices today. For one, there are practical constraints. For example, regarding the implementation of micro-level measurement burst cycles, the possibility to model people's emotional trajectory online (needed to instantaneously detect abrupt changes in affect), is currently lacking in standard ESM applications. Similarly, in the context of anchoring idiosyncratic emotional assessments, installing input-output dependencies between consecutive measurements is not straightforward with modern ESM software. Technical advances are needed to remove these barriers.

Second, some of the design strategies presented challenge the way ESM researchers traditionally model affect dynamics. For example, tracking people's emotional reaction in response to an impactful stressor likely yields time series that are not stationary, violating a statistical assumption that underlies some of the commonly investigated affect dynamics (e.g., emotional inertia or network density; Bringmann et al., 2013; Pe et al., 2015). Relatedly, the repeated use of measurement burst cycles violates the assumption of equally spaced time points, preventing for instance a standard assessment of people's global level of emotional instability (Jahng et al., 2008). In sum, potential adjustments to traditional ESM designs will close the door for some commonly studied affect dynamic metrics. At the same time, however, novel design strategies allow researchers to model dynamical patterns in affect in a more nuanced and fine-grained manner.

7.5 Conclusion

When interested in the real-life dynamics of emotion, this book chapter invites ESM researchers to raise the bar when it comes to the data quality of their studies. The SNR in traditional ESM research is typically substandard, which demands future daily life studies to experiment with more exotic design approaches to effectively disentangle people's true emotional reactions form inevitable background noise. Only then will we be able to reliably assess the internal and external validity of real-life affect dynamics.

References

Anderson, D. J., & Adolphs, R. (2014). A framework for studying emotions across species. *Cell, 157*, 187–200.

Beal, J. (2015). Signal-to-noise ratio measures efficacy of biological computing devices and circuits. *Frontiers in Bioengineering and Biotechnology, 3*, 93.

Boker, S. M., Molenaar, P. C. M., & Nesselroade, J. R. (2009). Issues in intraindividual variability: Individual differences in equilibria and dynamics over multiple time scales. *Psychology and Aging, 24*, 858–862.

Bos, E. H., de Jonge, P., & Cox, R. F. A. (2019). Affective variability in depression: Revisiting the inertia–instability paradox. *British Journal of Psychology, 110*, 814–827.

Bringmann, L. F., Pe, M. L., Vissers, N., Ceulemans, E., Borsboom, D., Vanpaemel, W., Tuerlinckx, F., & Kuppens, P. (2016). Assessing temporal emotion dynamics using networks. *Assessment, 23*, 425–435.

Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., Borsboom, D., & Tuerlinckx, F. (2013). A network approach to psychopathology: New insights into clinical longitudinal data. *PLoS One, 8*, e60188.

Bulteel, K., Mestdagh, M., Tuerlinckx, F., & Ceulemans, E. (2018). VAR(1) based models do not always outpredict AR(1) models in typical psychological applications. *Psychological Methods, 23*, 740–756.

Chow, S.-M., Ram, N., Boker, S. M., Fujita, F., & Clore, G. (2005). Emotion as a thermostat: Representing emotion regulation using a damped oscillator model. *Emotion, 5*, 208–225.

Cole, P. M., & Hollenstein, T. (2018). *Emotion regulation: A matter of time*. Routledge.

Dejonckheere, E., Mestdagh, M., Houben, M., Erbas, Y., Pe, M., Koval, P., Brose, A., Bastian, B., & Kuppens, P. (2018). The bipolarity of affect and depressive symptoms. *Journal of Personality and Social Psychology, 114*, 323–341.

Dejonckheere, E., Mestdagh, M., Houben, M., Rutten, I., Sels, L., Kuppens, P., & Tuerlinckx, F. (2019a). Complex affect dynamic measures add limited information to the prediction of psychological well-being. *Nature Human Behaviour, 3*, 478–491.

Dejonckheere, E., Mestdagh, M., Kuppens, P., & Tuerlinckx, F. (2020). Reply to: Context matters for affective chronometry. *Nature Human Behaviour, 4*, 690–693.

Dejonckheere, E., Mestdagh, M., Verdonck, S., Lafit, G., Ceulemans, E., Bastian, B., & Kalokerinos, E. K. (2019b). The relation between positive and negative affect becomes more negative in response to personally relevant events. *Emotion, 21*(2), 326–336.

Dejonckheere, E., Houben M., Schat, E., Ceulemans, E., & Kuppens, P. (2021). The short-term psychological impact of the COVID-19 pandemic in psychiatric patients: Evidence for differential emotion and symptom trajectories in Belgium. *Psychologica Belgica, 60*, 1–10.

Eisele, G., Vachon, H., Lafit, G., Kuppens, P., Houben, M., Myin-Germeys, I., & Viechtbauer, W. (2020). The effects of sampling frequency and questionnaire length on perceived burden, compliance, and careless responding in experience sampling data in a student population. *Assessment*.

Folkman, S. (1997). Positive psychological states and coping with severe stress. *Social Science and Medicine, 45*, 1207–1221.

Frijda, N. H. (1988). The laws of emotion. *American Psychologist, 43*, 349–358.

Fuller-Tyszkiewicz, M., Skouteris, H., Richardson, B., Blore, J., Holmes, M., & Mills, J. (2013). Does the burden of the experience sampling method undermine data quality in state body image research? *Body Image, 10*, 607–613.

Headey, B., & Wearing, A. (1989). Personality, life events, and subjective well-being: Toward a dynamic equilibrium model. *Journal of Personality and Social Psychology, 57*, 731–739.

Hemenover, S. H. (2003). Individual differences in rate of affect change: Studies in affective chronometry. *Journal of Personality and Social Psychology, 85*, 121–131.

Hisler, G. C., Krizan, Z., DeHart, T., & Wright, A. G. C. (2020). Neuroticism as the intensity, reactivity, and variability in day-to-day affect. *Journal of Research in Personality, 87*, 103964.

Houben, M., Van den Noortgate, W., & Kuppens, P. (2015). The relation between short-term emotion dynamics and psychological well-being: A meta-analysis. *Psychological Bulletin, 141*, 901–930.

Jahng, S., Wood, P. K., & Trull, T. J. (2008). Analysis of affective instability in ecological momentary assessment: Indices using successive difference and group comparison via multilevel modeling. *Psychological Methods, 13*, 354–375.

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science, 306*, 1776–1780.

Kalokerinos, E. K., Murphy, S. C., Koval, P., Bailen, N. H., Crombez, G., Hollenstein, T., Gleeson, J., Thompson, R. J., Van Ryckeghem, D. M. L., Kuppens, P., & Bastian, B. (2020). Neuroticism may not reflect emotional variability. *Proceedings of the National Academy of Sciences, 117*, 9270–9276.

Kalokerinos, E. K., Erbas, Y., Ceulemans, E., & Kuppens, P. (2019). Differentiate to regulate: Low negative emotion differentiation is associated with ineffective use but not selection of emotion-regulation strategies. *Psychological Science, 30*, 863–879.

Kalokerinos, E. K., Tamir, M., & Kuppens, P. (2017). Instrumental motives in negative emotion regulation in daily life: Frequency, consistency, and predictors. *Emotion, 4*, 648–657.

Koval, P., Brose, A., Pe, M. L., Houben, M., Erbas, Y., Champagne, D., & Kuppens, P. (2015). Emotional inertia and external events: The roles of exposure, reactivity, and recovery. *Emotion, 15*, 625–636.

Koval, P., & Kuppens, P. (2012). Changing emotion dynamics: Individual differences in the effect of anticipatory social stress on emotional inertia. *Emotion, 12*, 256–267.

Kuiper, R. M., & Ryan, O. (2018). Drawing conclusions from cross-lagged relationships: Re-considering the role of the time-interval. *Structural Equation Modeling: A Multidisciplinary Journal, 25*, 809–823.

Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010a). Emotional inertia and psychological maladjustment. *Psychological Science, 21*, 984–991.

Kuppens, P., Oravecz, Z., & Tuerlinckx, F. (2010b). Feelings change: Accounting for individual differences in the temporal dynamics of affect. *Journal of Personality and Social Psychology, 99*, 1042–1060.

Lapate, R. C., & Heller, A. S. (2020). Context matters for affective chronometry. *Nature Human Behaviour, 4*, 688–689.

Loossens, T., Mestdagh, M., Dejonckheere, E., Kuppens, P., Tuerlinckx, F., & Verdonck, S. (2020). The affective ising model: A computational account of human affect dynamics. *PLoS Computational Biology, 16*, e1007860.

MacCann, C., Erbas, Y., Dejonckheere, E., Minbashian, A., Kuppens, P., & Fayn, K. (2020). Emotional intelligence relates to emotions, emotion dynamics and emotion complexity: A meta-analysis and experience sampling study. *European Journal of Psychological Assessment, 36*, 460–470.

Metalsky, G. I., Joiner, T. E., Hardin, T. S., & Abramson, L. Y. (1993). Depressive reactions to failure in a naturalistic setting: A test of the hopelessness and self-esteem theories of depression. *Journal of Abnormal Psychology, 102*, 101–109.

Myin-Germeys, I., Kasanova, Z., Vaessen, T., Vachon, H., Kirtley, O., Viechtbauer, W., & Reininghaus, U. (2018). Experience sampling methodology in mental health research: New insights and technical developments. *World Psychiatry, 17*, 123–132.

Murray, G., Nicholas, C. L., Kleiman, J., Dwyer, R., Carrington, M. J., Allen, N. B., & Trinder, J. (2009). Nature's clocks and human mood: The circadian system modulates reward motivation. *Emotion, 9*, 705–716.

Nunnally, J. C. (1994). *Psychometric theory* (3rd ed.). Tata McGraw-Hill Education.

Oravecz, Z., Tuerlinckx, F., & Vandekerckhove, J. (2009). A hierarchical ornstein–uhlenbeck model for continuous repeated measurement data. *Psychometrika, 74*, 395–418.

Pe, M., Kircanski, K., Thompson, R. J., Bringmann, L. F., Tuerlinckx, F., Mestdagh, M., Mata, J., Jaeggi, S. M., Buschkuehl, M., Jonides, J., Kuppens, P., & Gotlib, I. H. (2015). Emotion-network density in major depressive disorder. *Clinical Psychological Science, 3*, 292–300.

Pe, M. L., & Kuppens, P. (2012). The dynamic interplay between emotions in daily life: Augmentation, blunting, and the role of appraisal overlap. *Emotion, 12*, 1320–1328.

Ram, N., Brinberg, M., Pincus, A. L., & Conroy, D. E. (2017). The questionable ecological validity of ecological momentary assessment: Considerations for design and analysis. *Research in Human Development, 14*, 253–270.

Robinson, M. D., Irvin, R. L., Persich, M. R., & Krishnakumar, S. (2020). Bipolar or independent? Relations between positive and negative affect vary by emotional intelligence. *Affective Science*.

Saothayanun, L., & Thangjai, W. (2018). Confidence intervals for the signal to noise ratio of two-parameter exponential distribution. In L. H. Anh, L. S. Dong, V. Kreinovich, & N. N. Thach (Eds.), *Econometrics for financial applications* (pp. 255–265). Springer International Publishing.

Schiepek, G., Aichhorn, W., Gruber, M., Strunk, G., Bachler, E., & Aas, B. (2016). Real-time monitoring of psychotherapeutic processes: Concept and compliance. *Frontiers in Psychology, 7*, 604.

Schimmack, U. (2003). Affect measurement in experience sampling research. *Journal of Happiness Studies, 4*, 79–106.

Schmidt, S. R., & Schmidt, C. R. (2016). The emotional carryover effect in memory for words. *Memory, 24*, 916–938.

Schuurman, N. K., & Hamaker, E. L. (2019). Measurement error and person-specific reliability in multilevel autoregressive modeling. *Psychological Methods, 24*, 70–91.

Schuurman, N. K., Houtveen, J. H., & Hamaker, E. L. (2015). Incorporating measurement error in N = 1 psychological autoregressive modeling. *Frontiers in Psychology, 6*, 1038.

Schwarz, N. (1999). Self-reports: How the questions shape the answers. *American Psychologist, 54*, 93–105.

Sels, L., Ceulemans, E., & Kuppens, P. (2017). Partner-expected affect: How you feel now is predicted by how your partner thought you felt before. *Emotion, 17*, 1066–1077.

Shojaei, E., Ashayeri, H., Jafari, Z., Zarrin Dast, M. R., & Kamali, K. (2016). Effect of signal to noise ratio on the speech perception ability of older adults. *Medical Journal of the Islamic Republic of Iran, 30*, 342.

Staudenmayer, J., & Buonaccorsi, J. P. (2005). Measurement error in linear autoregressive models. *Journal of the American Statistical Association, 100*, 841–852.

Stawski, R. S., MacDonald, S. W. S., & Sliwinski, M. J. (2015). Measurement burst design. In *The encyclopedia of adulthood and aging* (pp. 1–5). American Cancer Society.

Stone, A. A., Broderick, J. E., Schwartz, J. E., Shiffman, S., Litcher-Kelly, L., & Calvanese, P. (2003). Intensive momentary reporting of pain with an electronic diary: Reactivity, compliance, and patient satisfaction. *Pain, 104*, 343–351.

Taquet, M., Quoidbach, J., Fried, E. I., & Goodwin, G. M. (2020). Mood homeostasis before and during the coronavirus disease 2019 (COVID-19) lockdown among students in The Netherlands. *JAMA Psychiatry.* https://doi.org/10.1001/jamapsychiatry.2020.2389

Trull, T. J., & Ebner-Priemer, U. W. (2009). Using experience sampling methods/ecological momentary assessment (ESM/EMA) in clinical assessment and clinical research: Introduction to the special section. *Psychological Assessment, 21*, 457–462.

Welvaert, M., & Rosseel, Y. (2013). On the definition of signal-to-noise ratio and contrast-to-noise ratio for fMRI data. *PLoS One, 8*, e77089.

Wendt, L. P., Wright, A. G. C., Pilkonis, P. A., Woods, W. C., Denissen, J., Kühnel, A., & Zimmerman, J. (2020). Indicators of affect dynamics: Structure, test-retest reliability, and personality correlates. *European Journal of Personality*. https://doi.org/10.1002/per.2277

Wichers, M., Groot, P. C., & Psychosystems, E. G. (2016). Critical slowing down as a personalized early warning signal for depression. *Psychotherapy and Psychosomatics, 85*, 114–116.

Yu, S., Dai, G., Wang, Z., Li, L., Wei, X., & Xie, Y. (2018). A consistency evaluation of signal-to-noise ratio in the quality assessment of human brain magnetic resonance images. *BMC Medical Imaging, 18*, 17.

Part III
Between-Person Dynamics

Chapter 8

Emotion Dynamics in Intimate Relationships: The Roles of Interdependence and Perceived Partner Responsiveness

Laura Sels, Harry T. Reis, Ashley K. Randall, and Lesley Verhofstadt

Abstract Emotions are not only fundamentally dynamic in nature in the sense of varying across time, but they are also fundamentally social, originating in and shaping our interpersonal processes. Interpersonal emotion dynamics refer to the ways in which emotions and emotional self-regulation are dynamically influenced by interactional partners, given the interdependence that exists between them. We begin this chapter by describing the premise for interpersonal emotion dynamics in intimate relationships, what interpersonal emotion dynamics constitute, and the state of the art in the fields of emotion science, relationship science, and interpersonal emotion dynamics. Next, we discuss two key themes that we believe promote theoretical integration among seemingly disparate strands of research (in emotion and relationship research), emphasizing the importance of interdependence and perceived partner responsiveness in the interpersonal emotion dynamics that characterize intimate relationships. The chapter concludes with recommendations for future research in this promising area.

L. Sels (✉) · L. Verhofstadt
Ghent University, Ghent, Belgium
e-mail: Laura.Sels@UGent.be; Lesley.Verhofstadt@UGent.be

H. T. Reis
University of Rochester, Rochester, NY, USA
e-mail: HReis@ur.rochester.edu

A. K. Randall
Arizona State University, Tucson, AZ, USA
e-mail: Ashley.K.Randall@asu.edu

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_8

8.1 Introduction

Scholars and practitioners working with individuals and couples both recognize that emotions are inherently social and should not be viewed as purely intrapsychic experiences, as they are elicited, managed, altered, and maintained in interactions and relationships with others (e.g., Clark et al., 2001; Frijda & Mesquita, 1994; Keltner & Haidt, 1999; Parkinson, 1996; Van Kleef, 2009). Emotions in intimate relationships[1] are especially of interest, because people experience, share, and regulate emotions most often and most intensely in the relationship with their intimate partner (Berscheid & Ammazzalorso, 2001; Knobloch & Metts, 2013; Mikulincer & Shaver, 2005; Schoebi & Randall, 2015). The emotional experiences between intimate partners (hereafter, partners) are continually emerging, fluctuating, and interacting across time, which contribute to the development and maintenance of these relationships (e.g., Clark et al., 2017a, b; Reis, 2014). As such, partners' interpersonal emotional experiences, conceptualized as interpersonal *emotion dynamics,* are dynamic in the sense of being context-dependent and thus continuously changing, and are thought to be crucial for both the individuals' and the relationship's well-being (Butler, 2011; Sbarra & Hazan, 2008). Moreover, interpersonal emotion dynamics are proposed to mediate the robust link between intimate relationship functioning and mental and physical health (e.g., Farrell et al., 2018; Sbarra & Coan, 2018). Therefore, advancing our understanding of how partners impact each other's emotions dynamically—automatically and deliberately, as described below—and advancing perspectives on how interpersonal emotion dynamics arise and are associated to well-being is critical for future progress in the study of emotion.

8.2 Why and How Do Partners Impact Each Other's Emotions?

A central premise in relationship science is that partners are interdependent (Rusbult & Van Lange, 2003), which indicates that each partner's experiences, as well as the emotions tied to those experiences, are linked. Said differently, partners influence each other in myriad and often profound ways. Consider the example of a cohabiting couple who have a baby. Because they must care for the baby, partners have to coordinate childcare, including changing diapers, staying up in the middle of the

---

[1] Intimate relationships are particularly close interpersonal relationships that are defined by deep knowledge, interdependence, shared commitment, and feelings of caring, trust, and responsiveness (Miller, 2014). In this chapter, we mainly focus on adult intimate relationships in the form of romantic relationships, and often give examples of heterosexual romantic relationships. However, this does not in any sense imply that the proposed concepts do not apply to more diverse romantic relationships or other types of close relationships (e.g., adult-caregivers and close friends).

night when the baby cries, arranging logistics such as daycare, and so on. Furthermore, given that the partners share a household, they may be likely to divide household labors and have pooled economical resources. Finally, they spend much of their time together, not only in joint activities such as visiting family and friends, but also in recreation and simply living everyday life in each other's presence. Thus, both partners are dependent on each other, and because they have an enormous ability to influence each other's functioning and well-being, they must balance their own and their partner's needs and goals. As such, intimate relationships are best conceptualized not in terms of two independent persons who occasionally influence each other but instead as interdependent subparts of a single system, in which the members of the system are strongly linked. This notion is reflected in many theories and frameworks on intimate relationships, such as the transactive goal dynamics theory (Fitzsimons et al., 2015), which defines partners as interdependent subparts of a single self-regulating system, and family systems theories, which consider the family as a unitary interacting system (Bateson, 1972; Von Bertalanffy, 1950).

Because of their interdependence, partners' emotions and subsequent well-being depend on each other's behavior to a large extent. For instance, over time, partners come to expect certain behaviors of each other and when these expectations are not fulfilled, emotional reactions are likely to occur (Berscheid & Ammazzalorso, 2001; Fehr & Harasymchuk, 2005). As an example, partners may elicit negative emotions in each other not only because of unmet needs, such as in the case of one partner not doing their household tasks (although this is of course culturally-dependent), but they can also elicit positive emotions in each other by exceeding expectations (e.g., by doing more than their share of the housework). Relatedly, partners can facilitate each other's goals (e.g., providing the partner with spare time by doing some of their tasks) or, in contrast, hampering their goal progress (e.g., demanding that the partner do time-consuming tasks when a difficult work assignment must be completed), which can result in the experience of positive or negative emotions, respectively (Fitzsimons et al., 2015; Verhofstadt et al., 2020).

In turn, the experience of emotions in relationships accounts for substantial variability in the quality of these relationships (Bradbury et al., 2000). For instance, positive emotions can enhance closeness and relationship quality by prompting behavior that encourages bonding (Sels et al., 2021; Shiota et al., 2004; Wei-Fang et al., 2019), whereas negative emotions can initiate destructive interaction cycles (Verhofstadt et al., 2020). Experiencing negative emotions is often detrimental for relationship quality and stability, although some studies suggest that under certain circumstances negative emotions can promote healthy change in intimate relationships and thereby improve relationship quality (for an overview, see Fincham & Beach, 1999). It bears mention that different types of negative emotion may serve different functions in intimate relationships. In this regard, the distinction between soft (e.g., feeling sad or hurt) and hard (e.g., feeling angry or aggravated) negative emotions seems particularly relevant (Sanford, 2007; Randall & Schoebi, 2015). For instance, the expression of sadness is more likely to be beneficial to a relationship than anger or disgust (Sanford & Rowatt, 2004), presumably because sadness is likely to foster a compassionate response, whereas anger is more likely to trigger defensiveness and distance.

Apart from partners' behaviors and subsequent emotional responses within the relationship, situations that occur outside the relationship, and the emotions these events engender, undoubtedly impact both partners because of their interdependence. For example, stress that one partner experiences outside of the relationship (i.e., external stress; Randall & Bodenmann, 2009) can spill over into the relationship, distressing both partners (stress crossover) (Bodenmann, 2005; Neff & Karney, 2007; Randall & Bodenmann, 2017). Similarly, happy occurrences in one partner's life can lead to shared positive emotions for both (Gable & Reis, 2010). Various mechanisms have been proposed to explain how emotions are carried over from one partner to the other. Of particular relevance to emotions dynamics, partners can use each other's emotional expression, communicated verbally or nonverbally, as information to help guide their appraisal of the event (Parkinson & Simons, 2009; Verhofstadt et al., 2016) or they can mirror their partner's emotions, which may lead them to experience similar feelings without having any idea why (Hatfield et al., 2014). Importantly, these processes typically happen almost immediately, so that they are best reflected in second-to-second-basis measurements. A good example of this is positivity resonance, which describes how one person's positive emotion inspires and amplifies the other person's positive emotion (Brown et al., 2021), which in turn further inspires and amplifies the first person's positive emotions, resulting in a cycle of biobehavioral synchrony (peoples' nonverbal behaviors, autonomic physiology, and neural firings sharing the same tempo) and mutual care (Fredrickson, 2013).

Beyond automatically influencing each other's emotions, partners can also turn to and rely on each other explicitly to regulate their emotions or try to deliberately impact the other partner's emotion (Luginbuehl & Schoebi, 2020), a process sometimes referred to as interpersonal emotion regulation (Zaki & Williams, 2013). Interpersonal emotion regulation refers to a goal-directed process in one partner (the regulator) that is driven by some kind of motive (Niven, 2017) to try to change the other partner's emotion. When a personally relevant event occurs, either negative or positive, people commonly turn to others to share their experiences, and for those in a romantic relationship, this is most often their partner (Rimé et al., 2020). For instance, when one feels overwhelmed by work responsibilities, people tend to turn to their partner for support (e.g., Collins et al., 2010; Sullivan & Davila, 2010). Another example occurs when people seek out their partner to share the news when good things happen, a process referred to as *capitalization* (Gable & Reis, 2010; Peters et al., 2018). For instance, when sharing the news of a job promotion, both the act of relating this information and the response of the partner—whether it is encouraging, disinterested, or disparaging—has important personal and interpersonal consequences (e.g., for the experience of positive emotions, self-esteem, intimacy, and relationship stability; for a review, see Gable & Reis, 2010). However, it must be noted that there is a lack of research on understanding whether or not partners are deliberately trying to alter each other's emotions (for a notable exception, see Ruan, 2021). Indeed, partners often influence one another's emotions even when they are not consciously trying to do so or when their partner is not aware of this influence (e.g., Fitzsimons & Finkel, 2011; Howland & Simpson, 2010).

In this chapter, we do not distinguish between automatic and deliberate processes of emotion dynamics (cf., Zaki & Williams, 2013); rather, in its broadest sense, our model of interpersonal *emotion dynamics* refers to the ways in which emotions and emotional self-regulation are dynamically—that is, in a continuous and context-dependent manner—influenced by partners (Reis, 2014). This definition captures the myriad forms of interconnection between partners' behavior and emotional experience. We note that this definition is consistent with several basic axioms of many family system theories, such as communication theory (Hargie, 2010; Watzlawick et al., 2011), which posits that every behavior in an interaction is a form of communication, such that non-communication is impossible, even through silence or avoiding conversation altogether (Watzlawick et al., 2007). Consequently, during interactions, even behavior intended to be non-communicative provides a message and therefore has (presumably unintended) effects or influence on the other person. This definition construes causality as bidirectional and reciprocal, with both partners continually influencing and responding to each other, resulting in cycles of mutual influence or reciprocal determination (e.g., Gottlieb & Halpern, 2002; Witherington, 2011).

8.3 Interpersonal Emotion Dynamics: State of the Art

To date, the study of interpersonal emotion dynamics has largely been represented in two fields: relationship science and emotion science.

8.3.1 Interpersonal Emotion Dynamics in Relationship Science

An abundance of research grounded in relationship science has shown that when partners become interdependent, they influence each other's emotions in numerous ways (see Reis, 2001, 2014). Indeed, the important link between emotions and intimate relationships has been well-recognized by relationship researchers, who widely acknowledge that intimate partners shape each other's emotional experience, and that in turn their emotional experiences shape their relationship (for overviews, see Berscheid & Ammazzalorso, 2001; Randall & Schoebi, 2018). Despite this, most relationship research on emotions has measured partners' emotional experiences and phenomena as one-time, momentary, or static between person differences, instead of investigating these processes from a dynamic perspective. For instance, partners' empathic responses have traditionally been examined as instantaneous phenomena (induced by a situation) or as a static personality trait (e.g., assessed by questionnaires; for an overview of experimental studies and assessments of individual differences in empathy, see Davis, 2018), instead of as a dynamic process that unfolds, fluctuates, and is shaped by social interaction (Main et al., 2017; Preston & Hofelich, 2012; Zaki et al., 2008). However, as demonstrated elsewhere in this volume, the fundamental nature of emotion is misconstrued when its dynamic nature is not taken into account (Kuppens, 2015).

Interpersonal emotional processes are dynamic processes of continuous attunement and are constinually being shaped by each partners' response (i.e., feedback loops; Butler & Randall, 2013). For example, the experience of 'chemistry' in relationships has been shown to reflect emotional synchrony between interacting parties, more so than either persons' individual emotional experience (Major et al., 2018; Reis et al., in press). To capture these temporal and interactive processes, repeated measurements of emotional experiences are needed, such as by using experience sampling methods or continuous physiological recording in natural settings or dyadic laboratory interactions (Mehl & Conner, 2012). Such methods allow researchers to measure emotions as they emerge, occur, and vary across time.

8.3.2 Interpersonal Emotion Dynamics in Emotion Science

The field of emotion science has traditionally emphasized individual or intrapersonal processes while ignoring emotion's fundamentally interpersonal nature (for comments on this issue, see, for example, Butler & Gross, 2009; Campos et al., 2011). However, in the context of relationships, emotion dynamics depend upon the interaction of individuals in the relationship (e.g., Butler, 2011). For instance, when one partner expresses their concerns about household tasks, the feedback provided by the partner, whether explicit (e.g., by verbally assuring) or implicit (e.g., by a subtle sigh) will have immediate consequences for the emotion experienced.

Nevertheless, most emotion research focuses on individuals, investigating how emotions impact, and are impacted by, processes operating within, but not between, persons (Parkinson & Manstead, 2015). Even in research that examines emotions in putatively social contexts, the most typical research designs examine the behavior of participants who are passive recipients of information about social events rather than active agents interacting with other persons in real-world or ecologically valid contexts (Fischer & Van Kleef, 2010).

In sum, a longstanding singular focus on understanding interpersonal emotion dynamics within relationship and emotion science has yielded an incomplete picture of what emotion is and how it unfolds in real life, restricting a full understanding of this important concept. Fortunately, with new theories and research methods coming to light, this situation has begun to change, as we describe in the sections that follow.

8.4 The Rise of Research on Interpersonal Emotion Dynamics

Research on interpersonal emotion dynamics has seen a significant increase in the past 10–15 years because of a growing awareness of the importance of this perspective and the availability of appropriate research technologies, methods, and statistical techniques (see Butler, 2018). Hand in hand with technology that has been created for collecting intensive longitudinal dyadic data that is capable of capturing real-time behaviors and emotions, methods to analyze and model interpersonal emotion dynamics are increasingly being developed and made accessible to a wide audience (Hamaker et al., 2015; Lougheed & Hollenstein, 2018). For instance, *rties* is an open-source R-package that provides tools for modeling interpersonal dynamics (Butler & Barnard, 2019) and Gridware is a free software program for graphically depicting real-time emotional dynamics (Hollenstein, 2013). Relatedly, flexible statistical and graphical methods such as dynamic systems models are proposed (Butner et al., 2018). As a result, researchers are increasingly able to study interpersonal emotion processes as dynamic interpersonal patterns that emerge between people, thus providing a richer and more nuanced understanding than prior work adopting static, instantaneous, or intrapersonal perspectives.

Most existing research on interpersonal emotion dynamics focuses on partners' interdependent emotional changes or how partners' emotions are linked across time (Butler, 2011; Randall & Schoebi, 2018). This work involves a broad range of timescales assessing emotional experiences, ranging from short-term, second-to-second assessments (e.g., Randall et al., 2013), to more long-term, weekly assessments (e.g., Cooper et al., 2020). For instance, using data collected four times a day for three consecutive days, Saxbe and Repetti (2010) examined the extent to which one person's cortisol levels and negative mood were associated with their partner's mood/cortisol levels. As another example, Schoebi (2008) examined people's sensitivity to their partner's emotions throughout daily life: how well does one person's change in emotions predict the partner's subsequent change in emotions? Such research on dynamic, direct emotional linkages revealed conflicting and ambiguous results about the occurrence, importance, and underlying mechanisms related to this question (for overviews, see Butler, 2017; Sels et al., 2018).[2]

On the one hand, results from these and other similar studies suggest that emotional linkage can emerge, especially for negative emotions (notwithstanding the limitation that most of this work has been conducted with different-gender couples residing in Western cultures). On the other hand, recent evidence suggests that many couples do not exhibit meaningful emotional linkages, at least in terms of the connections (e.g., linear correlations between partners' emotions) or contexts (e.g., dyadic lab interactions or daily life) that researchers have most often examined (Sels et al., 2020). Further, sometimes emotional interdependence reveals no association with relationship and individual well-being (e.g., relationship satisfaction

---

[2] For a review with similar conclusions for physiological linkages, see Timmons et al. (2015).

and depression; Sels et al., 2016), whereas at other times emotional interdependence appears to be indicative of both positive (e.g., cooperation, Randall et al., 2013, or interpersonal sensitivity, Schoebi, 2008) and negative relational and individual functioning (e.g., insecure attachment, Butner et al., 2007, and stress, Neff & Karney, 2007). These seemingly contradictory findings present challenges to the study of interpersonal emotion dynamics and have forced researchers to step away from a primarily descriptive approach to a more theoretically defined account (Butler, 2017), to which we hope to contribute in this chapter.

8.5 Challenges in Studying Interpersonal Emotion Dynamics

Among the multiple challenges faced by researchers interested in the study of interpersonal emotion is the need to identify underlying situational, contextual, and personal factors that give rise to the various patterns of interpersonal emotion dynamics that have been documented (Randall & Schoebi, 2018) For instance, emotional linkages between partners can appear not only because of actual influence but also because of emotional similarity, which might reflect assortative mating (Feng & Baker, 1994; Gonzaga et al., 2010; Luo & Klohnen, 2005; Noel & Nyhan, 2011; Segrin, 2004). Furthermore, because intimate partners tend to live in close physical proximity, sharing environments and experiences that they may interpret in similar fashions, they may display similar emotional rhythms (Anderson et al., 2003; Gonzaga et al., 2007). In other examples, similar patterns of interpersonal emotion dynamics can arise because of automatic and unconscious emotional influences or because of deliberate influences, and because of emotions attributable to factors outside or within the relationship (Butler, 2015). Therefore, finding the appropriate match between theoretical interpretation and descriptive patterns of interpersonal emotion dynamics can be challenging, just as is deciding on the right level of specificity (Butler, 2018). For example, should a researcher focus on specific patterns restricted to discrete emotions, to the broader categories of negative versus positive emotions, to specific temporal linkages, or to specific contexts?

Another relevant challenge is intrinsic to the literature itself. In its earliest stages, research on interpersonal emotion dynamics suffered from a lack of shared language and an absence of overarching theories and research on mechanisms (Butler, 2011, 2018; Butler & Randall, 2013). As a result, knowledge accumulation was hampered. Fortunately, scholars are beginning to develop frameworks that provide broadly useful models for describing, understanding, and testing interpersonal emotion dynamics. For example, the *Situation-Context-Person Framework of* Interpersonal *Emotion Dynamics* (SCOPE) framework aims to disentangle situational (e.g., support vs. conflict interactions), contextual (e.g., degree of interdependence), and personal (e.g., attachment style) factors that may contribute to patterns of interpersonal emotion dynamics within close relationships over time (Randall & Schoebi, 2018). Importantly, this model explicitly acknowledges that these factors interact to initiate, shape, and modulate partners' emotional experiences, both within an interaction and relationship over time. Also, it has been proposed that long-standing theoretical models from relationship and emotion science can be integrated in emotion dynamics research to help researchers understand how partners continuously impact each other's emotions, such as the social baseline theory (Beckes & Coan, 2011), attachment theory (Bowlby, 2005), relational regulation theory (Lakey & Orehek, 2011), and socio-functional accounts (Keltner & Haidt, 1999; for overviews, see Luginbuehl & Schoebi, 2018; Randall & Schoebi, 2018).

Aiming to further advance research on interpersonal emotion dynamics and the association with well-being, we next discuss two key themes or assumptions that often seem to underlie theories and empirical work on dynamic emotional processes in intimate relationships.

8.6 Underlying Assumptions About Interpersonal Emotion Dynamics and Well-Being

Two discernible although often implicit assumptions pertain to existing theory and research on the nature of interpersonal emotion dynamics and its association with individual and relational well-being. First, partners' emotions are continuously influenced by one another, which can both enhance or reduce individual and relational well-being. Second, the outcomes associated with interpersonal emotion dynamics may depend on the responsiveness of the partners.

Starting with the first assumption, we have described above (under "Why and How Do Partners' Emotions Impact One Another?") how partners' interdependence leads to a continuous process of influencing each other's emotions. In that section, we reviewed literature showing that these influences can result in both improved and worsened moods, depending on what exactly is transpiring between the partners. Importantly, this indicates that interpersonal emotion dynamics are neither inherently good nor bad.

Partners can differ in the strength with which their emotions and emotional well-being are generally dependent on each other, and this can both hamper and facilitate their well-being over time. In formal terms, couples can be conceptualized as higher-order dynamic emotional systems that differ in the strength of their emotional interdependence (i.e., the degree to which the partners tend to impact each other's emotions) (e.g., Butler, 2011; Sels et al., 2016, 2018). The strength of this interdependence is a characteristic of the dyad and may be associated with the quality of their individual and relationship functioning, both good and bad. For example, strong connections can help partners to down-regulate each other's emotions in periods of stress, but can also cause them to become stuck in destructive patterns such as co-rumination or reciprocal negative affect. Timmons et al. (2015) reviewed evidence showing that the strength of physiological linkage (focusing on covariation between partners' physiological state for different types of physiological characteristics such as cortisol, heart rate, and testosterone) between intimate partners was both negatively (e.g., linkage in cortisol was negatively associated with relationship satisfaction) and positively (e.g., linkage in multiple systems was positively associated with the ability to identify the emotions of one's partner) associated with relationship processes, suggesting that indeed such linkage may confer benefits, but also may put couples at risk if they become entrenched in patterns of conflict or distress.

This conceptualization of couples as higher-order dynamic emotional systems is similar to the conceptualization of goals in the transactive goal dynamics theory (Fitzsimons et al., 2015). According to this theory, the extent to which partners have strong links among their goals is referred to as goal interdependence (or transactive density). Goal interdependence is expected to result in "good" outcomes when partners coordinate well, efficiently drawing on the collective resources afforded by interdependence to better accomplish their goals (e.g., when partners distribute household tasks in line with each partner's strengths or preferences). In these cases, partners experience transactive gain, or achieve better outcomes than they would individually. However, when partners have high goal interdependence but their coordination is inefficient, they may experience transactive loss and achieve worse outcomes than they would individually—for example, when the household division of labor primarily falls on one person against that person's will. Effective coordination in an interdependent dyad is defined by having shared goal representations (agreeing on what goals to pursue; e.g., do they both want a child) and mutual relationship orientation (e.g., both partners being committed to the relationship). Importantly, when partners offer each other goal-relevant support (e.g., minding the children while the partner works on her dissertation), this support is experienced as responsive to current goals and promotes perceived efficacy, availability of resources, and desired interdependence (Fitzsimons & Finkel, 2018).

This principle brings us to the second assumption. The outcomes associated with interpersonal emotion dynamics are expected to depend on partners' responsiveness to each other. Recognizing their interdependence, partners can act responsively, taking each other's needs, goals, preferences, and emotions into account, or they can act as independent individuals, which is likely to result in conflict and suboptimal outcomes (Rusbult et al., 2001). For example, in the context of a partner experiencing work-related stress, the non-stressed partner can be responsive to their partner's emotional experience, aiming to understand, validate, and care for their needs, or they can act unresponsively, such as by misunderstanding the partner or by being dismissive or critical (Bodenmann et al., 2019). Imagine a couple, Luca and Emma, who are highly emotionally interdependent but low in responsiveness. If Luca experiences a distressing event, her expressions of negative affect are likely to elicit negative feelings in Emma. Instead of aiming to understand and support her distressed partner, Emma is likely to respond by feeling distressed herself, and perhaps even personally attacked, leading to unresponsive behavior that fosters an escalating negativity cycle between both partners. On the other hand, in the same case but now characterized by high levels of responsiveness, Luca's communication of distress may arouse negative emotions in Emma, but it is also likely to elicit empathic concern and supportive behaviors that helps downregulate Luca's negative emotions. Crucially, the effectiveness of Emma's support depends on whether Luca experiences her support as responsive to her needs—after all, if what Emma offers is not what Luca feels she needs, it is unlikely that her distress would abate. In this way, the important moderating role of *perceived partner responsiveness* may help explain some of the conflicting results, described above, that have been found on emotional interdependence and relationship processes in intimate partners, with high emotional interdependence showing associations with both beneficial and negative relationship processes. As such, we posit that the explicit inclusion of a clear conceptualization of responsiveness is key to advancing knowledge about interpersonal emotion dynamics, and their implications for well-being.

8.7 Introducing Perceived Partner Responsiveness to Interpersonal Emotion Dynamics

Perceived partner responsiveness, a core integrative construct that encompasses many processes in relationship science, describes a process in which individuals come to believe that their relational partner attends to and supports core aspects of their selves: their needs, goals, preferences, and personal welfare (Laurenceau et al., 1998; Reis et al., 2004; Reis & Shaver, 1988). Perceived partner responsiveness is intrinsically tied to emotional processes, as it becomes relevant whenever interactions have implications for the partners' concerns and well-being, and thus, when these interactions elicit emotions, the partner's response engenders further emotions (e.g., feeling loved or unloved, supported or unsupported, feeling gratitude; Algoe et al., 2013; Reis et al., 2004).

To be more specific, in every interaction in which a person discloses personally relevant information to one's partner, such as important feelings, thoughts, needs, or concerns, the partner's response is important to the associated outcomes. By expressing important aspects of the self, disclosers give listeners an opportunity to enact responsiveness by showing understanding, validation, and care, or, alternatively, to withhold such responsiveness (Reis & Shaver, 1988). Understanding means that the partner "gets things right" and shows accurate insight into the matters that the discloser is sharing. Validation indicates that the partner values and respects the discloser's perspective, and caring refers to affection and concern for the discloser's well-being. It is important to recognize that the emotional impact of enacted responsiveness depends on whether that responsiveness is, or is not, perceived as such. That is, although extensive evidence indicates that perceived partner responsiveness is grounded in reality (see Reis et al., 2004, for a review), it is also substantially influenced by characteristics of the perceiver, such as their personality and situationally activated motives (Lemay & Clark, 2015; Reis & Clark, 2013).

Perceived partner responsiveness has been shown to predict numerous beneficial outcomes, such as intimacy (Laurenceau et al., 2004), emotional well-being and happiness (Selcuk & Karagobek, 2018), emotional openness (Ruan et al., 2020), personal growth and sleep efficiency (Selcuk et al., 2017), self-esteem (Cortes &

Wood, 2018; Murray et al., 2000), and even lower mortality risk (Selcuk & Ong, 2013). In this vein, and supporting our proposal about the relevance of responsiveness to interpersonal emotion dynamics, research shows that perceived partner responsiveness to emotional self-disclosures are more strongly tied to important relational outcomes such as intimacy than to factual self-disclosures (Laurenceau et al., 1998).

We are not the first to emphasize the necessity of attending to partners' responsiveness in understanding people's emotional lives. Clark et al. (2001) have argued that perceiving that another person will be responsive to one's needs influences the expression and experience of emotions, presumably because the target's expected responsiveness lessens concerns about potential vulnerability. In turn, feeling responsible for another person's needs also influences the experience and expression of certain emotions. For instance, people are more willing to express emotions that reveal weaknesses when they perceive those partners to be more responsive to them (Von Culin et al., 2018) and experience more gratitude towards these persons (Algoe et al., 2008). At the same time, people also experience certain relational emotions, such as happiness (Boothby & Clark, 2018), guilt (Baumeister et al., 1994; Baumeister & Leary, 1995), more often in relationships in which they feel responsible for their partner's needs than in other relationships, and apparently construe their emotional experiences and expressions as signals of caring about the other person (Clark et al., 2001). Further, perceived partner responsiveness is expected to affect emotion regulation, with responsive partners more often attempting to regulate their partner's emotions beneficially (Clark et al., 2017a, b; Reis, 2014).

Accumulating research identifies explicit links between interpersonal emotion dynamics, perceived partner responsiveness, and well-being. For example, in one recent study, individual differences in intrapersonal emotion dynamics—emotional inertia or the extent to which emotions are resistant to change—were associated with less perceived partner responsiveness and relationship satisfaction (Luginbuehl & Schoebi, 2020). This research suggests that when appropriate emotional responding to one's environment is hampered, the quality of one's interpersonal relationships is impaired. Specifically, this research showed that a lack of emotional responses to situations that one considers important for the relationship, such as conflicts, may lead to perceiving the partner as unresponsive.

Other studies reveal dynamic associations between emotion regulation and perceived partner responsiveness. For example, higher responsiveness predicts greater emotional expression (Ruan et al., 2020), while perceiving lower regard by partners predicts more expressive suppression and lower conflict resolution (Thomson et al., 2018). In addition, perceived partner responsiveness seems to impact the effects of emotion regulation, as perceived partner responsiveness recently has been shown to moderate associations between emotional coping strategies and negative emotional responses to stress (Kane et al., 2019). In the reverse causal direction, in dyadic interactions, positive emotions predict higher intentions to be responsive whereas negative emotions predict lower intentions (Lin et al., 2019).

8.8 Implications and Future Directions

As the field of interpersonal emotion dynamics evolves, additional research is needed on developing theories and testing frameworks (e.g., SCOPE; Randall & Schoebi, 2018) that can help elucidate important mechanisms that link relationships to various health outcomes. In reviewing recent work on interpersonal emotion dynamics, we identified several key themes. In particular, we argued that because partners are interdependent, their emotions are continuously influenced by each other, and these dynamic influences can result in enhanced or reduced well-being, depending in part on perceived partner responsiveness. By identifying these themes, we hope to inspire additional targeted research in this area. Given that interpersonal emotion dynamics can only be properly understood within their relational context it is crucial to integrate existing work in systematic, coherent accounts, supplemented by theory-driven studies that investigate the operation and impact of interpersonal emotion dynamics. Here, we describe several questions that we think are important to address as the field moves toward a comprehensive understanding of interpersonal emotion dynamics.

8.8.1 Widening the Scope of Interpersonal Emotion Dynamics

Empirical research to date has mainly focused on interpersonal emotion dynamics in the sense of direct emotion-to-emotion linkages or emotional interdependence. To some extent, this focus has distracted researchers from other ways in which partners may impact each other's emotions over time. For instance, a partner's responsive touch has been shown to predict enhanced positive emotions in daily life, and this association is mediated by psychological intimacy, which is closely related to perceived partner responsiveness (Debrot et al., 2013). Another example is suggested by research on non-conscious activation of interpersonal goals, which has shown that priming individuals with representations of significant others can activate goals, and hence emotions, related to that individual (Fitzsimons & Bargh, 2003).

Important in this regard is accounting for the role of perceived partner responsiveness in investigations of interpersonal emotion dynamics. We see three components of emotion that seem particularly relevant to perceived partner responsiveness and that warrant attention in future research: (1) emotional expressions, (2) empathic accuracy or actual empathic understanding, and (3) perceived empathic understanding. First, with regard to emotional expressions, opportunities for responsiveness arise when important, vulnerable aspects of a person, such as emotions or needs, are expressed towards the partner (i.e., personal self-disclosure). For example, social support attempts are typically initiated when partners communicate personal difficulties to each other (Sullivan & Davila, 2010). Relatedly, when something positive occurs, such as a personal success or triumph, partners have an opportunity to respond responsively (Gable et al., 2006). In fact, socio-functional accounts of emotions posit that emotions serve primarily a communicative function and are meant to improve interpersonal relationships (e.g., Fischer & Manstead, 2008; Keltner & Haidt, 1999; Niedenthal & Brauer, 2012). If so, how the partner responds to the communication plays a crucial role in determining whether or not the relationship benefits.

Second, empathic accuracy reflects partners' ablity to accurately assess the specific content of the feelings that are experienced by the discloser during interactions, as these emotions occur. Empathic accuracy (Ickes, 1993) is a form of cognitive empathy and determines how responsive a listener can be and how well understood the discloser is likely to feel (e.g., Gregory et al., 2019; Zaki et al., 2008). However, although an accurate empathic understanding seems necessary to be able to respond responsively, recent research suggests that it is not sufficient, but that it must be combined with the right motivation in order to result in responsive behavior; that is, an intent to be supportive is also imperative (Winczewski et al., 2016).

Lastly, empathic accuracy may or may not be perceived as such by the discloser, depending on the circumstances, motives, and skills of the interacting persons. Evidence strongly indicates that felt (or perceived) empathic understanding matters most for people's well-being (Hinnekens et al., 2019; Pollmann & Finkenauer, 2009; Reis et al., 2017; Simpson et al., 2003). The distinction between actual empathic accuracy and felt empathic understanding is important because people can feel understood in the absence of actual understanding, and because people can feel misunderstood even when their partner accurately understands their emotional state. Thus, it is not surprising that actual and perceived understanding are only modestly correlated (Hinnekens et al., 2019; Pollmann & Finkenauer, 2009).

8.8.2 The Importance of Perceptions

An additional consideration for future research is based on the importance of perceptions, and, more generally, the role of perceptions in interpersonal emotion dynamics. Extensive research has shown that people in satisfied relationships tend to see their partner more positively than warranted, and these perceptual biases in turn help keep the relationship happy and committed (Lemay & Clark, 2015; Murray & Holmes, 2017). With regard to emotions specifically, intimate partners may project their own emotions onto one another (e.g., Clark et al., 2017b), a tendency that is exacerbated by certain individual differences. For example, avoidantly attached individuals tend to perceive more negative emotions in their partners (Overall et al., 2015). In the first evidence for the importance of perceived interpersonal emotion dynamics, we showed in a recent study that both accurately perceiving and overestimating emotional similarity positively predicted experienced closeness towards a partner, while actual emotional similarity only predicted closeness through its effect on perception (Sels et al., 2020). A similar effect has been found for similarity in other domains, such as sexual similarity (de Jong & Reis, 2014). Further, interpersonal emotion dynamics may also help us better understand how people's emotions are influenced by their expectations about how their behavior will affect their partner's emotions. For instance, recent work on partner buffering suggests that some people find ways to emotionally and behaviorally regulate their insecurely attached partners, which helps such partners to feel better and behave more responsively (Arriaga et al., 2018; Simpson & Overall, 2014).

8.8.3 The Need for More Diverse and Clinical Samples

Investigations of interpersonal emotion dynamics have been mainly limited to homogenous, so-called WEIRD (Western, educated, industrialized, rich, and democratic) samples, which largely neglect cultural-contextual influences that seem likely to impact interpersonal emotion dynamics, perhaps profoundly so (Henrich et al., 2010). If researchers wish to construct a truly generalizable science, empirical studies on diverse populations are needed (Arnett, 2016; Roberts et al., 2020). For instance, same-gender couples experience unique external stressors stemming from their sexual minority status, which might affect the way in which stress spills over from one partner to the other (Cooper et al., 2020). By the same token, interpersonal emotion dynamics are inherently influenced by culture, broadly defined. Different cultural values, goals, norms, and practices in intimate relationships result in important cultural differences in emotional experiences (Mesquita et al., 2016). As a result, interpersonal emotion dynamics are best understood through the cultural lens in which they occur (Boiger & Mesquita, 2012; Mesquita & Boiger, 2014). By studying interpersonal emotion dynamics with more diverse samples, we can advance understanding of how specific experiences and cultural influences, broadly defined, may give rise to and affect interpersonal emotion dynamics and resulting associations.

Relatedly, a majority of research on interpersonal emotion dynamics has focused on healthy couples, largely overlooking clinical (i.e., more emotionally distressed) couples. However, determining how interpersonal emotion dynamics operate for individuals with diagnosed mental illness may be critical before implementing interventions and trainings. Moreover, it seems likely that information gleaned from couples facing relationship distress or in which one of the partners has serious mental health issues can provide key insights about how emotions ebb and flow across partners in all relationships. As such, it is important to consider how the social aspects of health interact with the biological and psychological, as described by the biopsychosocial model (Bodenmann & Randall, 2013; Lehman et al., 2017).

8.8.4 A Focus on Mechanisms

Finally, we suggest that a crucial next step will involve investigating interpersonal emotion dynamics as underlying mechanisms and explicit mechanisms of change in relationship development, maintenance, and longevity. Most interpersonal emotion dynamics research consists of correlational studies, but there is a need for experimental and long-term longitudinal studies, so that causal relationships can be uncovered (for notable exceptions, see e.g., Randall & Schoebi, 2015; Rohrbaugh et al., 2009). Such knowledge would be valuable for informing clinical practice and the design of couple therapies and preventive interventions. In this light, we note that many couple therapies emphasize emotional processes such as emotional disclosure and understanding, and responsiveness (Benson et al., 2012; Christensen, 2010; Sprenkle & Blow, 2004). In their work on extracting common principles that underlie specific couple therapies, Benson et al. (2012) state that "while the exact rationale and technique may differ by therapy, most couple therapies do seek to elicit private thoughts and emotions and encourage appropriate partner responsiveness to those expressions" (p. 29) Dynamic emotional processes are indeed central elements in couple therapies such as Emotionally Focused Couple Therapy (Johnson & Greenman, 2006), Insight Oriented Couple Therapy (Snyder et al., 1991), Integrative Behavioral Couples Therapy (Roddy et al., 2016), and Acceptance and Commitment Therapy (Hayes et al., 2009). This commonality suggests that a better understanding of interpersonal emotion dynamics in intimate relationships will be fruitful in advancing these treatment methods.

Initial evidence on interpersonal emotion dynamics also suggest the potential of targetting interpersonal emotion dynamics in intimate relationships. For instance, the Couple Coping Enhancement Training (CCET) program explicitly focuses on enhancing the disclosure of stress-related emotions and an accurate partner understanding of these disclosures, and has been shown to reduce marital distress and increased marital satisfaction (Bodenmann & Shantinath, 2004). Likewise, a partner-assisted emotional disclosure intervention in people with cancer has shown significant improvements in relationship quality and intimacy, especially when the patient initially reported holding back from discussing cancer-related concerns (Porter et al., 2009, 2012). Similarly, feeling well understood, a central component of perceived partner responsiveness, is associated with better marital quality in patients having end-of-live discussions with their spouses (Moorman, 2011). Finally, there is some process research showing that changes in specific emotional processes during emotion-focused and integrative behavioral couple therapies predict therapy outcomes (e.g., Cordova et al., 1998; McKinnon & Greenberg, 2017). These studies illustrate the potential for improving psychological interventions by focusing on interpersonal emotion dynamics.

8.9 Conclusion

This chapter presented a comprehensive account of the importance of considering emotion dynamics in relational contexts. Our review indicates that the intrinsic dynamic link between emotional experiences and intimate relationships should not be overlooked. As the promising field of interpersonal emotion dynamics is on the rise and is becoming integrated across disciplines and fields, we hope to have contributed to its advancement by identifying underlying key themes (interdependence and perceived partner responsiveness), and suggesting new directions for future research.

References

Algoe, S. B., Fredrickson, B. L., & Gable, S. L. (2013). The social functions of the emotion of gratitude via expression. *Emotion, 13*(4), 605–609. https://doi.org/10.1037/a0032701

Algoe, S. B., Haidt, J., & Gable, S. L. (2008). Beyond reciprocity: Gratitude and relationships in everyday life. *Emotion, 8*(3), 425–429. https://doi.org/10.1037/1528-3542.8.3.425

Anderson, C., Keltner, D., & John, O. P. (2003). Emotional convergence between people over time. *Journal of Personality and Social Psychology, 84*(5), 1054–1068. https://doi.org/10.1037/0022-3514.84.5.1054

Arnett, J. J. (2016). The neglected 95%: Why American psychology needs to become less American. In A. E. Kazdin (Ed.), *Methodological issues and strategies in clinical research* (pp. 115–132). American Psychological Association. https://doi.org/10.1037/14805-008

Arriaga, X. B., Kumashiro, M., Simpson, J. A., & Overall, N. C. (2018). Revising working models across time: Relationship situations that enhance attachment security. *Personality and Social Psychology Review, 22*(1), 71–96. https://doi.org/10.1177/1088868317705257

Bateson, G. (1972). The logical categories of learning and communication. In *Steps to an ecology of mind* (pp. 279–308).

Baumeister, R. F., & Leary, M. R. (1995). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin, 117*(3), 497–529.

Baumeister, R. F., Stillwell, A. M., & Heatherton, T. F. (1994). Guilt: An interpersonal approach. *Psychological Bulletin, 115*(2), 243–267. https://doi.org/10.1037/0033-2909.115.2.243

Benson, L. A., McGinn, M. M., & Christensen, A. (2012). Common principles of couple therapy. *Behavior Therapy, 43*(1), 25–35. https://doi.org/10.1016/j.beth.2010.12.009

Berscheid, E., & Ammazzalorso, H. (2001). Emotional experience in close relationships. In *Blackwell handbook of social psychology: Interpersonal processes* (pp. 308–330). Blackwell Publishers. https://doi.org/10.1002/9780470998557

Beckes, L., & Coan, J. A. (2011). Social baseline theory: The role of social proximity in emotion and economy of action. *Social and Personality Psychology Compass, 5*(12), 976–988. https://doi.org/10.1111/j.1751-9004.2011.00400.x

Bodenmann, G., & Randall, A. K. (2013). Close relationships in psychiatric disorders. *Current Opinion in Psychiatry, 26*(5), 464–467. https://doi.org/10.1097/YCO.0b013e3283642de7

Bodenmann, G. (2005). Dyadic coping and its significance for marital functioning. In T. A. Revenson, K. Kayser, & G. Bodenmann (Eds.), *Decade of behavior. Couples coping with stress: Emerging perspectives on dyadic coping* (pp. 33–49). American Psychological Association. https://doi.org/10.1037/11031-002

Bodenmann, G., Falconier, M. K., & Randall, A. K. (2019). Dyadic coping. *Frontiers in Psychology, 10*, 1984. https://doi.org/10.3389/fpsyg.2019.01498

Bodenmann, G., & Shantinath, S. D. (2004). The Couples Coping Enhancement training (CCET): A new approach to prevention of marital distress based upon stress and coping. *Family Relations, 53*, 477–484. https://doi.org/10.1111/j.0197-6664.2004.00056.x

Boiger, M., & Mesquita, B. (2012). The construction of emotion in interactions, relationships, and cultures. *Emotion Review, 4*(3), 221–229. https://doi.org/10.1177/1754073912439765

Boothby, E. J., & Clark, M. S. (2018). Side by side: How merely being with a close other can enhance well-being. In D. S. Dunn (Ed.), *Frontiers of social psychology. Postive psychology: Established and emerging issues* (pp. 80–93). Routledge/Taylor & Francis Group.

Bowlby, J. A. (2005). *A secure base: Clinical applications of attachment theory* (Vol. 939). Taylor & Francis.

Bradbury, T. N., Fincham, F. D., & Beach, S. R. (2000). Research on the nature and determinants of marital satisfaction: A decade in review. *Journal of Marriage and Family, 62*(4), 964–980. https://doi.org/10.1111/j.1741-3737.2000.00964.x

Brown, C. L., Chen, K.-H., Otero, M. C., Wells, J. L., Connelly, D., Levenson, R. W., & Fredrickson, B. L. (2021). Moments of co-experienced affect, more than individuallyexperienced affect, linked to relationship quality across conversational contexts. *Emotion*. https://doi.org/10.1037/emo0000939.

Butner, J. E., Crenshaw, A. O., Munion, A. K., Wong, A., & Baucom, B. R. (2018). *Simplifying the complexity of interpersonal emotion dynamics with regression graphics. Studies in emotion and social interaction-Second series. Interpersonal emotion dynamics in close relationships* (pp. 47–74). Cambridge University Press.

Butler, E. A. (2011). Temporal interpersonal emotion systems: The "ties" that form relationships. *Personality and Social Psychology Review, 15*(4), 367–393. https://doi.org/10.1177/1088868311411164

Butler, E. A. (2015). Interpersonal affect dynamics: It takes two (and time) to tango. *Emotion Review, 7*(4), 336–341. https://doi.org/10.1177/1754073915590622

Butler, E. A. (2017). Emotions are temporal interpersonal systems. *Current Opinion in Psychology, 17*, 129–134. https://doi.org/10.1016/j.copsyc.2017.07.005

Butler, E. A. (2018). Next steps toward understanding interpersonal emotion dynamics. In A. K. Randall & D. Schoebi (Eds.), *Interpersonal emotion dynamics in close relationships* (pp. 179–188). Cambridge University Press.

Butler, E. A., & Barnard, J. K. (2019). Quantifying interpersonal dynamics for studying socio-emotional processes and adverse health behaviors. *Psychosomatic Medicine, 81*(8), 749–758. https://doi.org/10.1097/PSY.0000000000000703

Butler, E. A., & Gross, J. J. (2009). Emotion and emotion regulation: Integrating individual and social levels of analysis. *Emotion Review, 1*(1), 86–87. https://doi.org/10.1177/1754073908099131

Butler, E. A., & Randall, A. K. (2013). Emotional coregulation in close relationships. *Emotion Review, 5*(2), 202–210. https://doi.org/10.1177/1754073912451630

Butner, J., Diamond, L. M., & Hicks, A. M. (2007). Attachment style and two forms of affect coregulation between romantic partners. *Personal Relationships, 14*(3), 431–455. https://doi.org/10.1111/j.1475-6811.2007.00164.x

Campos, J. J., Walle, E. A., Dahl, A., & Main, A. (2011). Reconceptualizing emotion regulation. *Emotion Review, 3*(1), 26–35. https://doi.org/10.1177/1754073910380975

Christensen, A. (2010). A unified protocol for couple therapy. In K. Hahlweg, M. Grawe-Berber, & D. H. Baucom (Eds.), *Enhancing couples: The shape of couple therapy to come* (pp. 33–46). Hogrefe Publishing.

Clark, M. S., Armentano, L. A., Boothby, E. J., & Hirsch, J. L. (2017a). Communal relational context (or lack thereof) shapes emotional lives. *Current Opinion in Psychology, 17*, 176–183. https://doi.org/10.1016/j.copsyc.2017.07.023

Clark, M. S., Fitness, J., & Brissette, I. (2001). Understanding people's perceptions of relationships is crucial to understanding their emotional lives. In G. J. Fletcher & M. S. Clark (Eds.), *Blackwell Handbook of Social Psychology: Interpersonal processes 2* (pp. 253–278). Blackwell Publishers. https://doi.org/10.1002/9780470998557

Clark, M. S., Von Culin, K. S., Clark-Polner, E., & Lemay, J. E. (2017b). Accuracy and projection in perceptions of partners' recent emotional experiences: Both minds matter. *Emotion*, 196–207. https://doi.org/10.1037/emo0000173

Collins, N. L., Ford, M. B., Guichard, A. C., Kane, H. S., & Feeney, B. C. (2010). Responding to need in intimate relationships: Social support and caregiving processes in couples. In M. Mikulincer & P. R. Shaver (Eds.), *Prosocial motives, emotions, and behavior: The better angels of our nature* (pp. 367–389). American Psychological Association.

Cooper, A. N., Tao, C., Totenhagen, C. J., Randall, A. K., & Holley, S. R. (2020). Daily stress spillover and crossover: Moderating effects of difficulties in emotion regulation in same-sex couples. *Journal of Personal and Social Relationships, 37*(4), 1245–1267. https://doi.org/10.1177/0265407519891777

Cordova, J. V., Jacobson, N. S., & Christensen, A. (1998). Acceptance versus change interventions in behavioral couple therapy: Impact on couples' in-session communication. *Journal of Marital and Family Therapy, 24*(4), 437–455. https://doi.org/10.1037/0022-006X.68.2.351

Cortes, K., & Wood, J. V. (2018). Is it really "all in their heads"? How self-esteem predicts partner responsiveness. *Journal of Personality, 86*(6), 990–1002. https://doi.org/10.1111/jopy.12370

Davis, M. H. (2018). *Empathy: A social psychological approach*. Routledge.

de Jong, D. C., & Reis, H. T. (2014). Sexual kindred spirits: Actual and overperceived similarity, complementarity, and partner accuracy in heterosexual couples. *Personality and Social Psychology Bulletin, 40*(10), 1316–1329. https://doi.org/10.1177/0146167214542801

Debrot, A., Schoebi, D., Perrez, M., & Horn, A. B. (2013). Touch as an interpersonal emotion regulation process in couples' daily lives: The mediating role of psychological intimacy. *Personality and Social Psychology Bulletin, 39*(10), 1373–1385. https://doi.org/10.1177/0146167213497592

Farrell, A. K., Imami, L., Stanton, S. C., & Slatcher, R. B. (2018). Affective processes as mediators of links between close relationships and physical health. *Social and Personality Psychology Compass, 12*(7), e12408. https://doi.org/10.1111/spc3.12408

Fehr, B., & Harasymchuk, C. (2005). The experience of emotion in close relationships: Toward an integration of the emotion-in-relationships and interpersonal script models. *Personal Relationships, 12*(2), 181–196. https://doi.org/10.1111/j.1350-4126.2005.00110.x

Feng, D., & Baker, L. (1994). Spouse similarity in attitudes, personality, and psychological well-being. *Behavior Genetics, 24*(4), 357–364.

Fincham, F. D., & Beach, S. R. (1999). Conflict in marriage: Implications for working with couples. *Annual Review in Psychology, 50*, 47–77. https://doi.org/10.1146/annurev.psych.50.1.47

Fischer, A. H., & Manstead, A. S. (2008). Social functions of emotion. In M. Lewis, J. M. Haviland-Jones, & L. F. Barrett (Eds.), *Handbook of emotions* (pp. 456–468). Guilford Press.

Fischer, A. H., & Van Kleef, G. A. (2010). Where have all the people gone? A plea for including social interaction in emotion research. *Emotion Review, 2*(3), 208–211. https://doi.org/10.1177/1754073910361980

Fitzsimons, G. M., & Bargh, J. A. (2003). Thinking of you: Nonconscious pursuit of interpersonal goals associated with relationship partners. *Journal of Personality and Social Psychology, 84*(1), 148–164. https://doi.org/10.1037/0022-3514.84.1.148

Fitzsimons, G. M., & Finkel, E. J. (2011). The effects of social relationships on self-regulation. In K. D. Vohs & R. F. Baumeister (Eds.), *Handbook of self-regulation: Research, theory, and applications* (pp. 390–406). The Guilford Press.

Fitzsimons, G. M., & Finkel, E. J. (2018). Transactive goal dynamics theory: A discipline-wide perspective. *Current Directions in Psychological Science, 27*(5), 332–338. https://doi.org/10.1177/0963721417754199

Fitzsimons, G. M., vanDellen, M. R., & Finkel, E. J. (2015). Transactive goal dynamics. *Psychological Review, 122*(4), 648–673. https://doi.org/10.1037/a0039654

Fredrickson, B. L. (2013). Positive emotions broaden and build. *Advances in Experimental Social Psychology, 47*, 1–53. https://doi.org/10.1016/B978-0-12-407236-7.00001-2

Frijda, N. H., & Mesquita, B. (1994). The social roles and functions of emotions. In S. Kitayama & H. R. Markus (Eds.), *Emotions and culture: Empirical studies of mutual influence* (pp. 51–87). American Psychological Association. https://doi.org/10.1037/10152-002

Gable, S., & Reis, H. T. (2010). Good news! Capitalizing on positive events in an interpersonal context. *Advances in Experimental Social Psychology, 42*, 195–257. https://doi.org/10.1016/S0065-2601(10)42004-3

Gable, S. L., Strachman, A., & Gonzaga, G. C. (2006). Will you be there for me when things go right? Supportive responses to positive event disclosures. *Journal of Personality and Social Psychology, 91*(5), 904–917. https://doi.org/10.1037/0022-3514.91.5.904

Gonzaga, G. C., Campos, B., & Bradbury, T. (2007). Similarity, convergence, and relationship satisfaction in dating and married couples. *Journal of Personality and Social Psychology, 93*(1), 34–48. https://doi.org/10.1037/0022-3514.93.1.34

Gonzaga, G. C., Carter, S., & Buckwalter, J. G. (2010). Assortative mating, convergence, and satisfaction in married couples. *Personal Relationships, 17*(4), 634–644. https://doi.org/10.1111/j.1475-6811.2010.01309.x

Gottlieb, G., & Halpern, C. T. (2002). A relational view of causality in normal and abnormal development. *Development and Psychopathology, 14*(3), 421–435. https://doi.org/10.1017/S0954579402003024

Gregory, A. J., Anderson, J. F., & Gable, S. L. (2019). You don't know how it feels: Accuracy in emotion perception predicts responsiveness of support. *Emotion*, 343–352. https://doi.org/10.1037/emo0000608

Hamaker, E. L., Ceulemans, E., & Grasman, R. P. (2015). Modeling affect dynamics: State of the art and future challenges. *Emotion Review, 7*(4), 316–322. https://doi.org/10.1177/1754073915590619

Hargie, O. (2010). *Skilled interpersonal communication: Research, theory, and practice*. Routledge.

Hatfield, E., Bensman, L., Thornton, P. D., & Rapson, R. L. (2014). New perspectives on emotional contagion: A review of classic and recent research on facial mimicry and contagion. *An International Journal on Personal Relationships*, 1981–6472. https://doi.org/10.23668/psycharchives.2195

Hayes, S. C., Strosahl, K. D., & Wilson, K. G. (2009). *Acceptance and commitment therapy*. American Psychological Association.

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). Most people are not WEIRD. *Nature, 466*(7302), 29–29. https://doi.org/10.1038/466029a

Hinnekens, C., Stas, L., Gistelinck, F., & Verhofstadt, L. L. (2019). "I think you understand me." Studying the associations between actual, assumed, and perceived understanding within couples. *European Journal of Social Psychology*, 1–15. https://doi.org/10.1002/ejsp.2614

Hollenstein, T. (2013). *State space grids*. Springer.

Howland, M., & Simpson, J. A. (2010). Getting in under the radar: A dyadic review of invisible support. *Psychological Science, 21*(12), 1878–1885. https://doi.org/10.1177/0956797610388817

Ickes, W. (1993). Empathic accuracy. *Journal of Personality, 61*(4), 587–610. https://doi.org/10.1111/j.1467-6494.1993.tb00783.x

Johnson, S. M., & Greenman, P. S. (2006). The path to a secure bond: Emotionally focused couple therapy. *Journal of Clinical Psychology, 62*(5), 597–609. https://doi.org/10.1002/jclp.20251

Kane, H. S., Wiley, J. F., & Schetter, C. D. (2019). The effects of interpersonal emotional expression, partner responsiveness and emotional approach coping on stress responses. *Emotion, 19*(8), 1315–1328. https://doi.org/10.1037/emo0000487

Keltner, D., & Haidt, J. (1999). Social functions of emotions at four levels of analysis. *Cognition and Emotion, 13*(5), 505–521. https://doi.org/10.1080/026999399379168

Knobloch, L. K., & Metts, S. (2013). Emotion in relationships. In J. A. Simpson & L. Campbell (Eds.), *The Oxford handbook of close relationships* (pp. 514–534). Oxford University Press.

Kuppens, P. (2015). It's about time: A special section on affect dynamics. *Emotion Review, 7*(4), 297–300. https://doi.org/10.1177/1754073915590947

Lakey, B., & Orehek, E. (2011). Relational regulation theory: A new approach to explain the link between perceived social support and mental health. *Psychological Review, 118*(3), 482–495. https://doi.org/10.1037/a0023477

Laurenceau, J. P., Rivera, L. M., Schaffer, A. R., & Pietromonaco, P. R. (2004). Intimacy as an interpersonal process: Current status and future directions. In D. J. Mashek & A. Aron (Eds.), *Handbook of closeness and intimacy* (pp. 61–78). Lawrence Erlbaum Associates, publishers.

Laurenceau, J.-P., Barrett, L. F., & Pietromonaco, P. R. (1998). Intimacy as an interpersonal process: The importance of self-disclosure, partner disclosure, and perceived partner responsiveness in interpersonal exchanges. *Journal of Personality and Social Psychology, 74*(5), 1238. https://doi.org/10.1037/0022-3514.74.5.1238

Lehman, B. J., David, D. M., & Gruber, J. A. (2017). Rethinking the biopsychosocial model of health: Understanding health as a dynamic system. *Social and Personality Psychology Compass, 11*(8), e12328. https://doi.org/10.1111/spc3.12328

Lemay, E. P., & Clark, M. S. (2015). Motivated cognition in relationships. *Current Opinion in Psychology, 1*, 72–75. https://doi.org/10.1016/j.copsyc.2014.11.002

Lin, W. F., Gosnell, C. L., & Gable, S. L. (2019). Goals, emotions, and the effort to be responsive during couple interactions. *Motivation and Emotion, 43*(2), 313–324. https://doi.org/10.1007/s11031-018-9731-1

Lougheed, J., & Hollenstein, T. (2018). Methodological approaches to studying interpersonal emotion dynamics. In A. Randall & D. Schoebi (Eds.), *Interpersonal emotion dynamics in close relationships* (p. 75). Cambridge University Press.

Luginbuehl, T., & Schoebi, D. (2018). Emotion dynamics and emotion regulation in intimate relationships. In P. M. Cole & T. Hollenstein (Eds.), *Emotion regulation: A matter of time* (pp. 208–225). Routledge.

Luginbuehl, T., & Schoebi, D. (2020). Emotion dynamics and responsiveness in intimate relationships. *Emotion, 20*(2), 133–148. https://doi.org/10.1037/emo0000540

Luo, S., & Klohnen, E. C. (2005). Assortative mating and marital quality in newlyweds: A couple-centered approach. *Journal of Personality and Social Psychology, 88*(2), 304. https://doi.org/10.1037/0022-3514.88.2.304

Main, A., Walle, E. A., Kho, C., & Halpern, J. (2017). The interpersonal functions of empathy: A relational perspective. *Emotion Review, 9*(4), 358–366. https://doi.org/10.1177/1754073916669440

Major, B. C., Le Nguyen, K. D., Lundberg, K. B., & Fredrickson, B. L. (2018). Well-being correlates of perceived positivity resonance: Evidence from trait and episode-level assessments. *Personality and Social Psychology Bulletin, 44*(12), 1631–1647. https://doi.org/10.1177/0146167218771324

McKinnon, J. M., & Greenberg, L. S. (2017). Vulnerable emotional expression in emotion focused couples therapy: Relating interactional processes to outcome. *Journal of Marital and Family Therapy, 43*(2), 198–212. https://doi.org/10.1111/jmft.12229

Mehl, M. R., & Conner, T. S. (2012). *Handbook of research methods for studying daily life*. Guilford Press.

Mesquita, B., & Boiger, M. (2014). Emotions in context: A sociodynamic model of emotions. *Emotion Review, 6*(4), 298–302. https://doi.org/10.1177/1754073914534480

Mesquita, B., Boiger, M., & De Leersnyder, J. (2016). The cultural construction of emotions. *Current Opinion in Psychology, 8*, 31–36. https://doi.org/10.1016/j.copsyc.2015.09.015

Mikulincer, M., & Shaver, P. R. (2005). Attachment theory and emotions in close relationships: Exploring the attachment-related dynamics of emotional reactions to relational events. *Personal Relationships, 12*(2), 149–168. https://doi.org/10.1111/j.1350-4126.2005.00108.x

Miller, R. (2014). *Intimate relationships*. McGraw-Hill Higher Education.

Moorman, S. M. (2011). The importance of feeling understood in marital conversations about end of life health care. *Journal of Social and Personal Relationships, 28*(1), 100–116. https://doi.org/10.1177/0265407510386137

Murray, S. L., & Holmes, J. G. (2017). *Motivated cognition in relationships: The pursuit of belonging*. Taylor & Francis.

Murray, S. L., Holmes, J. G., & Griffin, D. W. (2000). Self-esteem and the quest for felt security: How perceived regard regulates attachment processes. *Journal of Personality and Social Psychology, 78*(3), 478–498. https://doi.org/10.1037/0022-3514.78.3.478

Neff, L. A., & Karney, B. R. (2007). Stress crossover in newlywed marriage: A longitudinal and dyadic perspective. *Journal of Marriage and Family, 69*(3), 594–607. https://doi.org/10.1111/j.1741-3737.2007.00394.x

Niedenthal, P. M., & Brauer, M. (2012). Social functionality of human emotion. *Annual Review of Psychology, 63*, 259–286. https://doi.org/10.1146/annurev.psych.121208.131605

Niven, K. (2017). The four key characteristics of interpersonal emotion regulation. *Current Opinion in Psychology, 17*, 89–93. https://doi.org/10.1016/j.copsyc.2017.06.015

Noel, H., & Nyhan, B. (2011). The "unfriending" problem; the consequences of homophily in friendship retention for causal estimates of social influence. *Social Networks, 33*(3), 211–218. https://doi.org/10.1016/j.socnet.2011.05.003

Overall, N. C., Fletcher, G. J., Simpson, J. A., & Fillo, J. (2015). Attachment insecurity, biased perceptions of romantic partners' negative emotions, and hostile relationship behavior. *Journal of Personality and Social Psychology, 108*(5), 730–749. https://doi.org/10.1037/a0038987

Parkinson, B. (1996). Emotions are social. *British Journal of Psychology, 87*(4), 663–683. https://doi.org/10.1111/j.2044-8295.1996.tb02615.x

Parkinson, B., & Manstead, A. S. (2015). Current emotion research in social psychology: Thinking about emotions and other people. *Emotion Review, 7*(4), 371–380. https://doi.org/10.1177/1754073915590624

Parkinson, B., & Simons, G. (2009). Affecting others: Social appraisal and emotion contagion in everyday decision making. *Personality and Social Psychology Bulletin, 35*(8), 1071–1084. https://doi.org/10.1177/0146167209336611

Peters, B. J., Reis, H. T., & Gable, S. L. (2018). Making the good even better: A review and theoretical model of interpersonal capitalization. *Social and Personality Psychology Compass, 12*(7), e12407. https://doi.org/10.1111/spc3.12407

Pollmann, M. M., & Finkenauer, C. (2009). Investigating the role of two types of understanding in relationship well-being: Understanding is more important than knowledge. *Personality and Social Psychology Bulletin, 35*(11), 1512–1527. https://doi.org/10.1177/0146167209342754

Porter, L. S., Baucom, D. H., Keefe, F. J., & Patterson, E. S. (2012). Reactions to a partner-assisted emotional disclosure intervention: Direct observation and self-report of patient and partner communication. *Journal of Marital and Family Therapy, 38*(s1), 284–295. https://doi.org/10.1111/j.1752-0606.2011.00278.x

Porter, L. S., Keefe, F. J., Baucom, D. H., Hurwitz, H., Moser, B., & Patterson, E. (2009). Partner-assisted emotional disclosure for patients with gastrointestinal cancer: Results from a randomized controlled trial. *Cancer, 115*(S18), 4326–4338. https://doi.org/10.1002/cncr.24578

Preston, S. D., & Hofelich, A. J. (2012). The many faces of empathy: Parsing empathic phenomena through a proximate dynamic-systems view of representing the other in the self. *Emotion Review, 4*(1), 24–33. https://doi.org/10.1177/1754073911421378

Randall, A., & Bodenmann, G. (2009). The role of stress on close relationships and marital satisfaction. *Clinical Psychology Review, 29*(2), 105–115. https://doi.org/10.1016/j.cpr.2008.10.004

Randall, A. K., & Bodenmann, G. (2017). Stress and its associations with relationship satisfaction. *Current Opinion in Psychology, 13*, 96–106. https://doi.org/10.1016/j.copsyc.2016.05.010

Randall, A. K., Post, J. H., Reed, R. G., & Butler, E. A. (2013). Cooperating with your romantic partner: Associations with interpersonal emotion coordination. *Journal of Social and Personal Relationships, 30*(8), 1072–1095. https://doi.org/10.1177/0265407513481864

Randall, A. K., & Schoebi, D. (2015). Lean on me: Susceptibility to partner affect attenuates psychological distress over a 12-month period. *Emotion, 15*(2), 201–210. https://doi.org/10.1037/emo0000043

Randall, A. K., & Schoebi, D. (2018). Interpersonal emotion dynamics in close relationships . Cambridge University Press.

Reis, H. T. (2001). Relationship experiences and emotional well-being. In C. D. Ryff & B. H. Singer (Eds.), *Emotion, social relationships, and health* (pp. 57–86). Oxford University Press.

Reis, H. T. (2014). Responsiveness: Affective interdependence in close relationships. In M. Mikulincer & P. R. Shaver (Eds.), *The Herzliya series on personality and social psychology. Mechanisms of social connection: From brain to group* (pp. 255–271). American Psychological Association.

Reis, H., & Clark, M. (2013). Responsiveness. In J. A. Simpson & L. Campbell (Eds.), *The Oxford handbook of close relationships* (pp. 400–423). Oxford University Press.

Reis, H. T., Clark, M. S., & Holmes, J. G. (2004). Perceived partner responsiveness as an organizing construct in the study of intimacy and closeness. In D. J. Mashek & A. P. Aron (Eds.), *Handbook of closeness and intimacy* (pp. 201–225). Lawrence Erlbaum Associates Publishers.

Reis, H. T., Lemay, E. P., Jr., & Finkenauer, C. (2017). Toward understanding understanding: The importance of feeling understood in relationships. *Social and Personality Psychology Compass, 11*(3), e12308. https://doi.org/10.1111/spc3.12308

Reis, H. T., Regan, A., & Lyuobomirsky, S. (in press). Interpersonal chemistry: What is it, how does it emerge, and how does it operate? Perspectives on Psychological Science. https://doi.org/10.31234/osf.io/c9djm.

Reis, H. T., & Shaver, P. (1988). Intimacy as an interpersonal process. In S. Duck, D. F. Hay, S. Hobfoll, W. Ickes, & B. Mongomery (Eds.), *Handbook of personal relationships: Theory, research and interventions* (pp. 367–389). John Wiley & Sons.

Rimé, B., Bouchat, P., Paquot, L., & Giglio, L. (2020). Intrapersonal, interpersonal, and social outcomes of the sharing of emotion. *Current Opinion in Psychology, 31*, 127–134. https://doi.org/10.1016/j.copsyc.2019.08.024

Roberts, S. O., Bareket-Shavit, C., Dollins, F. A., Goldie, P. D., & Mortenson, E. (2020). Racial inequality in psychological research: Trends of the past and recommendations for the future. *Perspectives on Psychological Science, 15*(6), 1295–1309. https://doi.org/10.1177/1745691620927709

Roddy, M., Nowlan, K. M., Doss, B. D., & Christensen, A. (2016). Integrative behavioral couple therapy: Theoretical background, empirical research, and dissemination. *Family Process, 55*(3), 408–422. https://doi.org/10.1111/famp.12223

Rohrbaugh, M. J., Shoham, V., Butler, E. A., Hasler, B. P., & Berman, J. S. (2009). Affective synchrony in dual-and single-smoker couples: Further evidence of "symptom-system fit"?. *Family process, 48*(1), 55–67. https://doi.org/10.1111/j.1545-5300.2009.01267.x

Ruan, Y. (2021). *Regulating the Emotions of Romantic Partners (Unpublished doctoral dissertation)*. Unversity of Rochester.

Ruan, Y., Reis, H. T., Clark, M. S., Hirsch, J. L., & Bink, B. D. (2020). Can I tell you how I feel? Perceived partner responsiveness encourages emotion expression. *Emotion, 20*(3), 329–342. https://doi.org/10.1037/emo0000650

Rusbult, C. E., & Van Lange, P. A. (2003). Interdependence, interaction, and relationships. *Annual Review of Psychology, 54*(1), 351–375.

Rusbult, C. E., Olsen, N., Davis, J. L., & Hannon, P. A. (2001). Commitment and relationship maintenance mechanisms. In Close romantic relationships (pp. 95–122). Psychology Press.

Sanford, K., & Rowatt, W. C. (2004). When is negative emotion positive for relationships? An investigation of married couples and roommates. *Personal Relationships, 11*(3), 329–354. https://doi.org/10.1111/j.1475-6811.2004.00086.x

Saxbe, D., & Repetti, R. L. (2010). For better or worse? Coregulation of couples' cortisol levels and mood states. *Journal of Personality and Social Psychology, 98*(1), 92–103. https://doi.org/10.1037/a0016959

Sbarra, D. A., & Coan, J. A. (2018). Relationships and health: The critical role of affective science. *Emotion Review, 10*(1), 40–54. https://doi.org/10.1177/1754073917696584

Sanford, K. (2007). Hard and soft emotion during conflict: Investigating married couples and other relationships. *Personal Relationships, 14*(1), 65–90. https://doi.org/10.1111/j.1475-6811.2006.00142.x

Sbarra, D. A., & Hazan, C. (2008). Coregulation, dysregulation, sef-regulation: An integrative analysis and empirical agenda for understanding adult attachment, separation, loss, and recovery. *Personality and Social Psychology Review, 12*(2), 141–167. https://doi.org/10.1177/1088868308315702

Schoebi, D. (2008). The coregulation of daily affect in marital relationships. *Journal of Family Psychology, 22*(4), 595–604. https://doi.org/10.1037/0893-3200.22.3.595

Schoebi, D., & Randall, A. K. (2015). Emotional dynamics in intimate relationships. *Emotion Review, 7*(4), 342–348. https://doi.org/10.1177/1754073915590620

Segrin, C. (2004). Concordance on negative emotion in close relationships: Transmission of emotion or assorative mating? *Journal of Social and Clinical Psychology, 23*(6), 836–856. https://doi.org/10.1521/jscp.23.6.836.54802

Selcuk, E., & Karagobek, A. B. (2018). Responsiveness as a key predictor of happiness: Mechanisms and unanswered questions. In D. Melikşah & N. Sümer (Eds.), *Close relationships and happiness across cultures* (pp. 1–18). Springer.

Selcuk, E., & Ong, A. D. (2013). Perceived partner responsiveness moderates the association between received emotional support and all-cause mortality. *Health Psychology, 32*(2), 231–235. https://doi.org/10.1037/a0028276

Selcuk, E., Stanton, S. C., Slatcher, R. B., & Ong, A. D. (2017). Perceived partner responsiveness predicts better sleep quality through lower anxiety. *Social Psychological and Personality Science, 8*(1), 83–92. https://doi.org/10.1177/1948550616662128

Sels, L., Cabrieto, J., Butler, E., Reis, H., Ceulemans, E., & Kuppens, P. (2020). The occurrence and correlates of emotional interdependence in romantic relationships. *Journal of Personality and Social Psychology, 119*(1), 136–158. https://doi.org/10.1037/pspi0000212

Sels, L., Ceulemans, E., Bulteel, K., & Kuppens, P. (2016). Emotional interdependence and well-being n close relationships. *Frontiers in Psychology, 7*, 283. https://doi.org/10.3389/fpsyg.2016.00283

Sels, L., Ceulemans, E., & Kuppens, P. (2018). A general framework for capturing interpersonal emotion dynamics. In A. Randall & D. Schoebi (Eds.), *Interpersonal emotion dynamics in close relationships* (pp. 27–46). Cambridge University Press.

Sels, L., Tran, A., Greenaway, K. H., Verhofstadt, L., & Kalokerinos, E. K. (2021). The social functions of positive emotions. *Current Opinion in Behavioral Sciences, 39*, 41–45. https://doi.org/10.1016/j.cobeha.2020.12.009

Shiota, M. N., Campos, B., Keltner, D., & Hertenstein, M. J. (2004). Positive emotion and the regulation of interpersonal relationships. In P. Philippot & R. S. Feldman (Eds.), *The regulation of emotion* (pp. 127–155). Lawrence Erlbaum Associates.

Simpson, J. A., & Overall, N. C. (2014). Partner buffering of attachment insecurity. *Current Directions in Psychological Science, 23*(1), 54–59. https://doi.org/10.1177/0963721413510933

Simpson, J. A., Orina, M. M., & Ickes, W. (2003). When accuracy hurts and when it helps: A test of the empathic accuracy model in marital interactions. *Journal of Personality and Social Psychology, 85*(5), 881–893. https://doi.org/10.1037/0022-3514.85.5.881

Snyder, D. K., Wills, R. M., & Grady-Fletcher, A. (1991). Long-term effectiveness of behavioral versus insight-oriented marital therapy: A 4-year follow-up study. *Journal of Consulting and Clinical Psychlogy, 59*(1), 138–141. https://doi.org/10.1037/0022-006X.59.1.138

Sprenkle, D. H., & Blow, A. J. (2004). Common factors and our sacred models. *Journal of Marital and Family Therapy, 30*(2), 113–129. https://doi.org/10.1111/j.1752-0606.2004.tb01228.x

Sullivan, K. T., & Davila, J. (2010). *Support processes in intimate relationships*. Oxford University Press.

Thomson, R. A., Overall, N. C., Cameron, L. D., & Low, R. S. (2018). Perceived regard, expressive suppression during conflict, and conflict resolution. *Journal of Family Psychology, 32*(6), 722–732. https://doi.org/10.1037/fam0000429

Timmons, A. C., Margolin, G., & Saxbe, D. E. (2015). Physiological linkage in couples and its implications for individual and interpersonal functioning: A literature review. *Journal of Family Psychology, 29*(5), 720–731. https://doi.org/10.1037/fam0000115

Van Kleef, G. A. (2009). How emotions regulate social life: The emotions as social information (EASI) model. *Current Directions in Psychological Science, 18*(3), 184–188. https://doi.org/10.1111/j.1467-8721.2009.01633.x

Verhofstadt, L., Devoldre, I., Buysse, A., Stevens, M., Hinnekens, C., & Ickes, W. (2016). The role of cognitive and affective empathy in spouses' support interactions: An observational study. *PLoS One*, e0149944. https://doi.org/10.1371/journal.pone.0149944

Verhofstadt, L., Lemmens, G., & Vanhee, G. (2020). Systemic research in individual, couple, and family therapy and counseling. In M. Ochs, M. Borcsa, & J. Schweitzer (Eds.), *European Family Therapy Association Series* (pp. 281–298). Springer.

Von Bertalanffy, L. (1950). An outline of general system theory. *British Journal for the Philosophy of Science, 1*, 134–165.

Von Culin, K. R., Hirsch, J. L., & Clark, M. S. (2018). Willingness to express emotion depends upon perceiving partner care. *Cognition and Emotion, 32*(3), 641–650. https://doi.org/10.1080/02699931.2017.1331906

Watzlawick, P., Beavin, J. B., & Jackson, D. D. (2011). *Pragmatics of human communication: A study of interactional patterns, pathologies, and paradoxes*. WW Norton & Company.

Watzlawick, P., Beavin, J. H., & Jackson, D. D. (2007). Some tentative axioms of communication. In R. T. Craig & H. L. Muller (Eds.), *Theorizing communication: Readings across traditions* (pp. 275–288). SAGE Publications.

Wei-Fang, L., Gosnell, C. L., & Gable, S. L. (2019). Goals, emotions, and the effort to be responsive during couple interactions. *Motivation and Emotion, 43*(2), 313–324. https://doi.org/10.1007/s11031-018-9731-1

Winczewski, L. A., Bowen, J. D., & Collins, N. L. (2016). Is empathic accuracy enough to facilitate responsive behavior in dyadic interaction? Distinguishing ability from motivation. *Psychological Science, 27*(3), 394–404. https://doi.org/10.1177/0956797615624491

Witherington, D. C. (2011). Taking emergence seriously: The centrality of circular causality for dynamic systems approaches to development. *Human Development, 54*(2), 66–92. https://doi.org/10.1159/000326814

Zaki, J., & Williams, W. C. (2013). Interpersonal emotion regulation. *Emotion, 13*(5), 803–810. https://doi.org/10.1037/a0033839

Zaki, J., Bolger, N., & Ochsner, K. (2008). It takes two: The interpersonal nature of empathic accuracy. *Psychological Science, 19*(4), 399–404. https://doi.org/10.1111/j.1467-9280.2008.02099.x

Chapter 9

A Mutualism, Affiliation and Status Seeking (MASS) Framework of Fundamental Affective Dynamics and Their Survival Benefits

Dean Mobbs, Sarah M. Tashjian, and Brian Silston

Abstract Primates have developed a unique set of complex drives for successful group living, yet theorists rarely contemplate their taxonomy and how such drives relate to affective dynamics fundamental for group success. Affective dynamics and drive fulfilment exert mutual influence on one another, ultimately collectively promoting or undermining survival. We first identify six core benefits of group living common among both humans and other animals, and from this foundation we propose three broad social drives that have evolved to preserve or enhance group living benefits: (1) Mutualism comprises cooperation, reciprocity, trust, and fairness; (2) Affiliation comprises assimilation and belonging, whereby one aims to fit into the group through adherence to group norms and ideologies; (3) Status-Seeking is represented by a drive to build one's value in the group and acquire differential access to mates and other resources. We identify affective dynamics that facilitate each social drive: (1) Reactive flexibility involves qualitative shifts in affect in response to shifting goals, which facilitates mutualism; (2) Affective synchrony is the reproduction of another individual's emotions in oneself and facilitates social affiliation; (3) Regulatory flexibility facilitates status-seeking through a broad repertoire of regulatory approaches during strategic behavioral pursuits. Finally, we posit that fulfilling Mutualism, Affiliation, and Status-Seeking (MASS) drives enhances the benefits of social living and supports development of fundamental affective dynamics.

D. Mobbs (✉) · S. M. Tashjian
Humanities and Social Sciences, California Institute of Technology (Caltech),
Pasadena, CA, USA
e-mail: dmobbs@caltech.edu; smtashji@caltech.edu

B. Silston
Department of Psychology, Columbia University, New York, NY, USA

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_9

9.1 Introduction

A preparedness for sociality is ubiquitous across organisms. At its most basic level, social behavior is observed in microbes and invertebrates (Anstey et al., 2009; Carlisle & Ellis, 1963; Henke & Bassler, 2004), yet becomes increasingly complex in rodents and non-human primates. Sociality is preeminent in humans and occurs early in development. Fetal twins, for example, show social interaction in the womb (Castiello et al., 2010), newborns show an instant preference for the human face (Valenza et al., 1996), infants quickly understand that others have inner minds (Onishi & Baillargeon, 2005) and exhibit complex social rules including egalitarianism and aversion to inequity (Fehr et al., 2008; Svetlova et al., 2010; Tomasello et al., 2005). While most other species have evolved to survive by winning power struggles and attraction contests over competitors, humans have evolved a prodigious social intelligence unmatched by other species. Social living necessarily involves affective dynamics—emotions are inherently social. Social others elicit emotions, emotions facilitate communication between individuals and groups, and emotion regulation influences behavior of others and social approval (van Kleef et al., 2016). Emotions that emphasize survival through development of social bonds and in response to social problems allow humans to transcend individual weaknesses and achieve unparalleled collective progress.

It has long been thought that survival needs drive the motivation system which in turn drives a set of rules for behavior (Maslow, 1943; Tolman, 1932). Here, we first establish the adaptive function of sociality by delineating a set of survival benefits conferred by the evolution of social groups, extending from the micro (i.e. individual) to the macro benefits of group living. Second, we propose three core social drives serving as the engines that motivate the successful acquisition of group living benefits. These drives include: Mutualism, Affiliation, and Status-Seeking (MASS drives). Third, we identify affective dynamics critical to and influenced by each social drive. Identifying and discerning the socio-affective features that facilitate the acquisition of group living benefits is a starting point from which to understand the evolution and organization of the human social brain.

9.2 Six Benefits of Group Living

Paleontologists have shown that the primate species have been living in groups for approximately 52 million years (Shultz et al., 2011). While the disadvantages to group living are apparent (e.g. competition, resource depletion and spread of disease), clear benefits do exist. We propose that the benefits of social living can be categorized into six core themes. Several of these benefits are universal, observed across multiple group living species and are basic social ingredients in promoting the survival of the species. These include anti-predation, increased mating opportunities, group aggression, social foraging, and decreased infant mortality (Alexander, 1974; Terborgh & Janson, 1986).

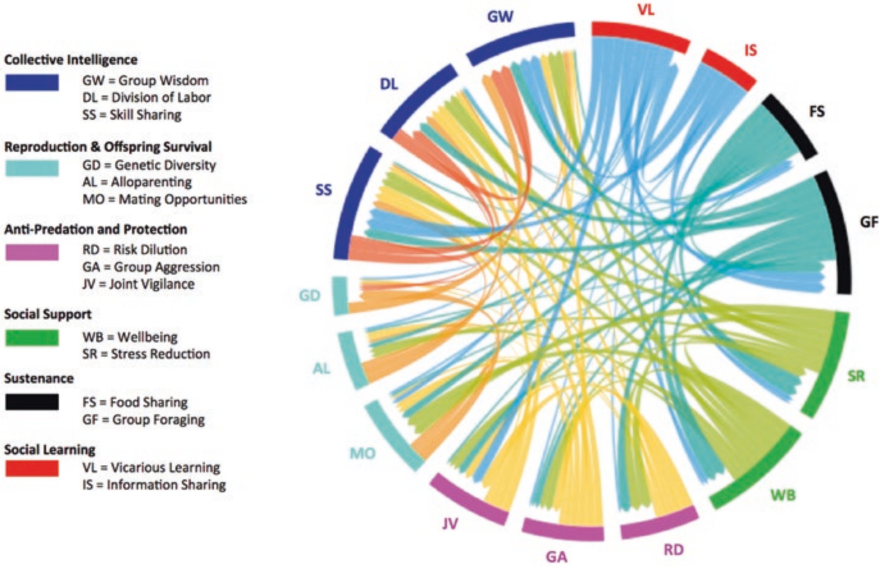


Fig. 9.1 The six benefits of group living and their interactions. Groupings are delineating by color—for example Collective Intelligence is represented by blue, and features Group Wisdom, Division of Labor and Skill Sharing. Thickness of the lines connecting different areas indicated the assumed strength of the interaction

In many other social animals, the benefits are much richer and extend to higher-order benefits including social learning, information sharing, social support and collective intelligence. Group benefits also include the ultimate evolutionary benefit of passing on one's genes, thereby defining sociality as an extremely useful engine to enhance the fitness of the individual, its kin and the species (Fig. 9.1). These six benefits include:

9.2.1 *Reproduction and Offspring Survival*

Mating Opportunities. The adaptive advantages of being in a larger group are more variety and greater access to mates, obvious benefits for both sexes.

Genetic Diversity. Shuffling of different genetic material leads to greater diversity, and can be described by Mixability Theory, which proposes that the breakdown of gene combinations results in maximization of fitness by finding the best combination of genes (Livnat et al., 2008); also see "Social Heterosis Theory" (Nonacs & Kapheim, 2007)).

Alloparenting. Cooperative breeding has traditionally been linked to kin-selection theory, in which animals exclusively help genetically related individuals. However, converging evidence shows that some species assist in the rearing of non-kin (Clutton-Brock, 2002).

9.2.2 Anti-predation and Protection

*Risk dilution and joint vigilance***.** The theory of risk dilution (i.e. safety in numbers) suggests that the larger the group of prey the smaller the chance a particular individual will fall victim to lethal attack by predators (Foster & Treherne, 1981). Social animals also frequently develop a system to alert others of danger.

*Group aggression***.** Group aggression is in effective way to acquire resources, increase protection, and reduce threat from enemies.

Stress reduction. Stress reduces with predation risk and increased availability of resources. Predation protection allows for free time to play, develop pedagogy, and engage in social learning.

9.2.3 Sustenance

Social *foraging.* Solitary foraging results in a clear disadvantage, placing the animal at increased risk of predation, starvation and reduced breadth of diet (Giraldeau, 1984; Krebs, 1972). Social foraging provides benefits to both the individual and the group, where others may have information about patches rich in food and patches with low risk of predation.

Food and resource sharing. Sharing of food and resources benefits individuals in times of need (e.g. food scarcity). Sharing is observed in hunter-gather populations (Gurven, 2004) and recent research shows that Chimpanzees will share food with non-kin (Pruetz & Lindshield, 2012) under certain circumstances.

9.2.4 Social Learning and Information Sharing

Vicarious learning. Social learning is defined as the organism's ability to receive, retain, learn from others, and the ability to reproduce the observed behaviour (Bandura, 1962). Social learning is also apparent in other animals, and especially useful in unpredictable environments.

Information Sharing. Social psychological research has shown the benefits of taking advice from others. For example, surrogate advice by others provides more accurate information than self-predictions in for novel event (Gilbert et al., 2009). These studies support the idea that information sharing is critical to how we interact with others and provides rich information that can enhance socially adaptive behaviours.

9.2.5 Wellbeing and Belonging

Wellbeing. Extensive research shows that quality of life increases with high quality social bonds and support. Comparative studies demonstrate how living in groups can promote physiological health (Seeman & McEwen, 1996) and reproductive success is significantly increased by the quality of relationships (Silk, 2007). In humans, poor social bonds can lead to poor health, social adjustment, and quality of life (Baumeister & Leary, 1995b). Indeed, recent studies have shown that social isolation and loneliness correlate with increased mortality (Steptoe et al., 2013), cardiovascular disease, higher blood pressure, heightened inflammatory responses to stress, and infection (Barth et al., 2010; Cohen et al., 1997; Eisenberger & Cole, 2012; Loucks et al., 2006).

Belonging. The need to belong is a fundamental human drive that leads to the formation of resilient relational bonds (Baumeister & Leary, 1995b). Belonging not only improves motivation, affect, and physical health, but connection to social others influences emotional experiences. For example, emotional and behavioral patterns flexibly adapt to group composition (Cottrell & Neuberg, 2005).

9.2.6 Collective Intelligence

Group Wisdom and Skill Sharing. Group wisdom was creatively demonstrated by Galton's simple, yet ingenious, "ox" guesstimation study, which showed that when a crowd were asked to guess the weight of an ox, the average group response was within one pound of its actual weight (Galton, 1907). More recently, Wegner and colleagues showed that when people are paired in couples, those in a relationship perform better on a joint memory task than two strangers, (Wegner et al., 1991) and Surowiecki (Surowiecki, 2004) showed that this group intelligence extends to such domains as stock markets and quiz shows. The ability and capacity to frequently select optimal choices for the group derives from variance afforded by numbers and comparative abilities.

Division of labour. Complex biological systems are characterized by self-organizing processes that include specialized and domain general subcomponents that confer efficiencies and advantages to the organism. These organizational processes include a division of labour observed in eusocial insect species and higher animals including birds and primates (Arnold et al., 2005; Torres et al., 2012).

9.3 Why a New Theory of Social Motives?

To realize the benefits of sociality described herein, a set of social drives must exist at the level of the individual to motivate successful integration and function within a social group. Several critical questions in psychology and neuroscience regarding the social nature of humans must be addressed to advance our understanding of human social motivation. These include: what motivates social behavior; why are some individuals good at social interaction while others are inept; and more generally, why are we social creatures? To probe these fundamental questions, we must consider the range and frequencies of human behaviors in social settings. Existing theories of social motivation have all contributed to understand these questions, however, meaningful differences between theories support the need for integration. Further, no obvious explanatory framework arises as to the requirements for the success of social groups, or the particular needs that evolved to contribute to success that provide reciprocal benefits to the individual and group. While Fiske's drives (Belonging, Understanding, Controlling, Enhancing Self and Trusting; BUCET; Fiske, 2002) are loosely linked to survival value of self, kin, and group, other theories have not made connections to group survival (e.g., Self-Determination Theory; Deci & Ryan, 2008) The ability of an individual to acquire the benefits outlined above depends on its success as a group living animal. In the next section, we argue that the benefits of social living can be mapped on to several core social drives.

9.4 Three Core Social drives: Mutualism, Affiliation and Status-Seeking (MASS)

We propose previous theories of social motivation can be consolidated into three core drives that coordinate the formation of individuals into social groups and thereby facilitate affective development and yield survival benefits. We use the broader term of 'Mutualism' to capture compliance and trusting drives (Deci & Ryan, 2008; Fiske, 2002). Relatedness, belonging, and understanding all point to a drive to form social ties (Deci & Ryan, 2008; McClelland, 1965). We adopt the term 'Affiliation' to encompass these drives. Existing theories also proposes a drive for power or control (Fiske, 2002; McClelland, 1965). We consolidate these into 'Status Seeking'. In contrast to previous theories, the MASS model encompasses individual and group interactions. The social dimension of group interactions necessitates addressing affective dynamics. Emotional feedback drives motivation in individuals within a group context to calibrate individual needs to optimize the dynamics for group success. Under this interactional feedback framework, we can explain why those of higher perceived status have greater influence, why we affiliate, why we act in mutually beneficial ways and how these together continually refine both individual and group level affective characteristics that result in social success. We point to reactive flexibility, affective synchrony, and regulatory flexibility as necessary for full realization of group-oriented survival benefits. Linking motivational drives to affective competencies accounts for substantial overlap between social and affective processes in the human brain. From this, we detail the three core social drives:

1. **Mutualism**: the drive toward mutually beneficial behaviours, such as reciprocal altruism, cooperation and collaboration. While upfront and sharing costs are

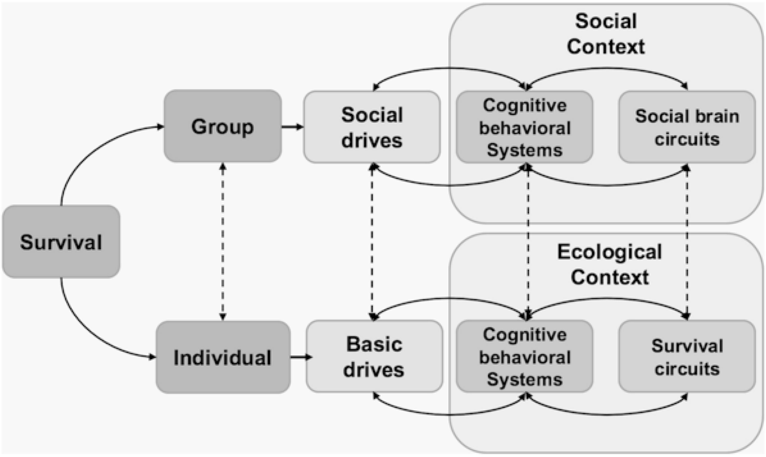


Fig. 9.2 Survival from social and basic drives. The individual's survival is supported by a set of basic drives including hunger, thirst, reproduction, thermoregulation, anti-predation (e.g. freezing, flight). The evocation of these basic drives is determined by several factors including the ecological context and the internal state of the organism (Mobbs, 2018). These are in turn supported by a set of behavioral, cognitive systems instantiated in survival circuits (see (LeDoux, 2012)). Social drives (e.g. MASS drives) are evoked in group living animals and have a distinct set of neural circuits. These social brain circuits are flexible and interact with basic drives (dotted lines). For example, both basic and social drives can up or down-regulate each other resulting in an interaction between survival circuits and higher level constructive circuits that underlie the social brain

incurred at the individual level, these factors benefit both the group and individual as a result of establishing trust and ability to accomplish more than any individual can alone. Social signals of benevolence increase the likelihood of accruing social support from other group members. Since most groups are small enough such that all individuals are acquainted, reputation can be generated and tracked by others, forming a basis for consistency and reliability among members.

2. **Affiliation**: the drive towards social bonds, as well as their maintenance via allegiance behaviours and adherence to group norms and ideologies. On a micro level, affiliation motivates selective bonding among a close-knit number of individuals (e.g. friends, romantic partners). On a macro-level this includes allegiance behaviors such as group pride and nationalism, and the basis for concepts such as ideology.
3. **Status-Seeking**: the drive to optimize the individual's relative standing within the group through competition, reputation-enhancement, and the signalling of prestige. Individuals high in social status possess greater ability to influence other group members, e.g. coalesce group motivations to pursue important causes, facilitate adherence to rules, the result of which can further increase affiliative behaviours and the effectiveness of collaboration (Fig. 9.2).

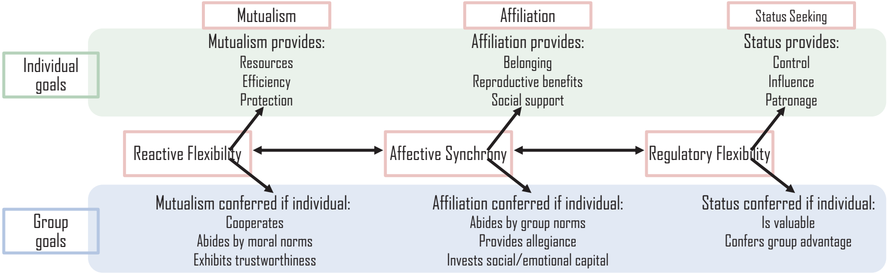


Fig. 9.3 Affective dynamics facilitate achievement of individual and group goals for each core social drive. Affective dynamics exert influence on one another such that individuals with high competency in one dynamic (e.g., reactive flexibility) likely have high competence in another (e.g., affective synchrony), thereby compounding the likelihood that they achieve their individual social goals and provide survival benefit to other group members

9.5 MASS Linked Affective Dynamics

As a basic proposition, affect serves a feedback function providing reinforcement or punishment for behavior. Affect encompasses both emotions, the labels given to experienced affect typically with specific origins, and moods, less intense and longer-lasting than emotions but with less obvious causes. Beyond simply tracking progress toward a goal (e.g., negative affect indicates a discrepancy between one's goal and current state), affect energizes behavior (Reeve, 2014). In social contexts, observing other's emotions serves as information about what behavior is acceptable (Heerdink et al., 2019). The ability to fulfil MASS drives relies, in part, on affective dynamics (Fig. 9.3). We propose three such dynamics corresponding with each MASS drive:

1. **Reactive** flexibility: the ability to change affective content (i.e., anger, happiness) and patterns in response to environmental demands. We propose a role for reactive flexibility in facilitating mutualism. An example of reactive flexibility during mutualism can be seen in shifting from negative to positive affective patterns after the resolution of conflict. Conversely, shifting from positive to negative affect patterns can facilitate mutualism by signalling to the counterpart that their uncooperative behaviour is unacceptable to the social group (Granic et al., 2007).
2. **Affective** synchrony: the reproduction of another individual's emotions in oneself. Individuals mimic emotions of social counterparts by partially activating the emotional state in themselves (Wood et al., 2016). This synchrony not only enables emotional inference, but also results in greater affiliation effects of collective social engagement (Páez et al., 2015). Synchrony may also promote maintenance of social bonds. For example, neural concordance is higher among closer friends (Hyon et al., 2020) and neural concordance in parent-child dyads

enhances development of emotional competence (Lee et al., 2017). Thus, socially proximate individuals may experience synchronous psychological states when exposed to common stimuli resulting in greater perception of affective synchrony thereby strengthening social bonds.

3. **Regulatory** flexibility: the ability to use a wide range of regulatory strategies depending on contextual demands, and to monitor and use affective feedback to promote goal pursuit (Bonanno & Burton, 2013). Across development, regulatory abilities predict future social skills and social outcomes (Blair et al., 2015), providing opportunity for status attainment and greater future influence. Different emotion regulation strategies confer different benefits. As such, access to distinct strategies facilitates context-dependent selection of emotional responses. Establishment of effortful strategies facilitates increasingly sophisticated and flexible pursuit of temporally distant and difficult goals, like status acquisition (Todd et al., 2012).

Although we propose a role for each affective dynamic within the MASS framework, these dynamics are not mutually exclusive. For example, cooperation generates shared emotional experiences as well as autonomic coupling (Vanutelli et al., 2017), identifying a role for affective synchrony in mutualism. Reactive flexibility is likely linked to social status via trustworthiness: perceived trustworthiness is higher for higher status individuals (Blue et al., 2020) and trustworthiness is associated with affective flexibility (Slepian & Carr, 2019). Regulatory flexibility is linked to a myriad of critical facets of successful social functioning including adaptive coping, cognitive control, and physiological regulation (Gross, 2015). Ultimately, the shared role of each affective dynamic across the MASS drives demonstrates the interconnected framework supporting these drives despite the separable benefits associated with each.

Although we propose that affective dynamics facilitate core MASS drives, social motives likely also support the evolution of affective dynamics. For each affective dynamic detailed above, bi-directional associations exist with MASS drives such that the survival value of social drives may have helped humans and other emotionally-rich species evolve complex affective systems. All organisms must have the ability to detect and respond to meaningful stimuli in order to survive. Neural systems associated with emotional experiences in humans underpin survival behaviors in humans and non-human animals (LeDoux, 2012). Van Kleef proposed in the Emotions As Social Information (EASI) Model that human emotional expressions affect social behavior by triggering affective reactions in others. Thus, MASS drives likely trigger engagement of certain affective systems to promote similar drive states in group affiliates. Emotions serve an individual function to aid in salience detection, motivation, and attentional allocation (Schwarz & Clore, 1983) and also a group function as implicit communication (Oatley & Johnson-laird, 1987). The drive for successful social living increase the utility of affective dynamics for survival.

9.6 Mutualism

Wilson and Wilson (Wilson & Wilson, 2007) propose that "…for a social group to function as an adaptive unit, its members must do things for each other". Mutualism is defined here as a situation in which individuals gain a net survival benefit from working together (Krebs & Davies, 1997) and propagates the group's success by minimizing self-serving behaviors. We therefore use the term mutualism to capture several related phenomena including cooperation, reciprocal altruism, symbiosis, and collaboration and synonymous with the term "mutual benefit" associated with +/+ behaviors; see (West et al., 2007). Mutualism is a critical aspect of social evolution as it reduces the likelihood of a "Tragedy of the Commons," whereby individuals act selfishly, in turn leading to resource reduction and collapse of society. Mutualism thus relies on reactive flexibility whereby individuals are able to adaptively shift affective states, as well as attention and behavior, in response to shifting group goals (Hollenstein, 2015). Mutualism may be distinguished from affiliation through tailoring of affective reactions. Reactive flexibility focuses on the modification of an individual's affective experience to further a common group goal whereas affective synchrony (prioritized for affiliation) is focused on mirroring another's emotions in oneself. Thus, understanding underlying affective dynamics can illuminate where social motives diverge depending on the affective function being prioritized. Not surprisingly, theorists have placed mutualism at the forefront of social brain evolution, which supports identification of and responding to the goals of others. Like other social animals, humans act mutually towards others through resource sharing, helping, cooperative breeding, and offspring protection. Mutualism also begins early in development. For example, human infants will help others at around the age of 14–18 months (Hepach et al., 2012). At around 15 months, infants have expectations concerning what is fair (Schmidt & Sommerville, 2011) and children between the ages of 3 and 8 years demonstrate an aversion to inequality (Fehr et al., 2008). We propose that mutualism takes several broad forms:

9.6.1 Collaboration, Cooperation and Trust

Haldane (Haldane, 1932) proposed that cooperation occurs when a behavior is "socially valuable, but individually disadvantageous". More recent theorists have proposed the "Interdependence Hypothesis", which posits that collaboration is critical to primate survival and procreation (Tomasello et al., 2012). Relatedly, the "Vygotskian Intelligence Theory" suggests that collaboration, communication and social learning are the reasons why primates evolved large brains and complex cognition (Moll & Tomasello, 2007). Tomasello and colleagues have suggested that human cooperation may have evolved in two key steps. First, during group foraging when hunting individuals were interdependent on each other and therefore cared about each other's welfare. Second, these new collaborative skills were "scaled up" for living in large groups and to face the challenge of competition from other groups (Tomasello et al., 2012). Such dependence on others would presumably increase prosocial behaviors, such as helping others achieve their goals and information sharing (Warneken & Tomasello, 2009). Mechanistically, the ability to identify and respond flexibility to the goals and affective sharing of others facilitates prosociality through development of empathy and perspective taking (Decety et al., 2016). At a meso level, unique cultural demands may also play a role in shaping the pressures for mutualistic behaviors. For example, Talheim and colleagues showed that the rice growing culture of Southern China, in contrast to the wheat-growing culture of Northern China, is built around interdependence, collaboration and holistic thinking (Talhelm et al., 2014).

Mutualistic behaviors depend on the ability of individuals to determine the likelihood and reliability that others will engage in reciprocal cooperative behaviors. According to Lawler's Affect Theory of Social Exchange, emotional experiences are key for cooperative relationships and act as reinforcements or punishments furthering mutualism (Lawler, 2001). Emotions are also subtle external signals about one's intentions. Reactive flexibility enhances the possibility for successful cooperation through the actor's adaptation to the intentions and goals of the social counterpart. High-variability in emotional expression leads to more positive perceptions of authenticity and greater trustworthiness perceptions (Slepian & Carr, 2019). Observing others' to determine trustworthiness comes with a time cost, but individuals that develop what McNamara and colleagues call a "social awareness" benefit a group by expediently observing and identifying trustworthy individuals (McNamara et al., 2009). It is worth noting that perceptions of trustworthiness may not accurately reflect a counterpart's willingness to cooperate, but rather index subjective impressions that garner high consensus (Rule et al., 2013), potentially detection of subtle emotional expressions (Oosterhof & Todorov, 2009).

9.6.2 Altruistic and Third Party Punishment

In order for group living to be successful, cooperation must be enforced by the punishment of defectors and free-riders. Recent evidence suggests that people cooperate at the start of N-Player Prisoner's Dilemma interactions, yet if players defect, collaborators will impose spiteful punishment (Fehr & Fischbacher, 2003). Likewise, when unfair players receive painful shocks, males, but not females, greet this with feelings of reward (Singer et al., 2006). In some cases, people will punish at a cost to themselves. Known as altruistic punishment, Fehr and Gacthter (Fehr & Gachter, 2002) have defined this as the situation whereby "individual punish, although the punishment is costly for them and yields no material gain" (p. 137). This is exemplified in the Ultimatum game, in which people will reject unfair offers and even punish at a financial cost to themselves (Guth et al., 1982; Yu et al., 2014).

Unfair offers induce anger and rejecting unfair relates to reactive aggression in the real world (Gilam et al., 2019). These studies support the notion that a set of punishment norms need to be in place to protect fairness and cooperation and that negative affective experiences can diminish mutualistic behavior after norms are violated. Third-party punishment, or punishment meted out by individuals that observe but are not a party to selfish behaviors results in greater cooperation, but also signals to others by virtue of the cost incurred that one is not selfish (Jordan et al., 2016a). This signal is also translated into the perception of trustworthiness, thus justifying the upfront cost given the high moral reputational value assigned by other group members.

9.6.3 Morality and Shared Values

Humans and nonhuman primates share a set of moral tendencies including a sense of fairness, empathy, forgiveness, and other social emotions that make living in groups a productive enterprise (de Waal, 2011). Moral beliefs are powerful filters that bias information processing and derive as a result of group or cultural norms that develop in relation to collective goals and evolve through time. Once these goals are defined, morality captures the value of actions taken to achieve them. Historically, human cultures made use of institutions of authority such as religions to dictate cultural norms and how these norms were established. These institutions have the advantage of solidifying social bonds among constituents that share in a belief system. Morality is present across human endeavors, where culture plays at times a strong role in tuning the values of individuals that belong to particular groups. Investigation of the neural correlates of moral decision-making reveals a complex, diverse and context specific process that is susceptible to external influences. Crockett has suggested that heuristic, automatic processes, deliberate consequentialist reasoning, and reflexive reasoning coexist in the moral thinking space (Crockett, 2013) while others offer a dynamic rather than a dual-process account (Van Bavel et al., 2015; Cushman, 2013). Experimental work suggests that individuals that bear a similar neural signature when participating in moral decision-making are remarkably consistent in moral tendencies, indicating that differences in moral preferences can be traced to differences in neural substrate and processing (Kappes et al., 2016). Thus shared values likely reflect shared or similar neurobiology and the associated affective profiles that motivate reasoning and decision-making processes (Feldman Hall & Mobbs, 2015). Although disagreement exists as to the role of emotion in mediating morality, lesion and patient studies from cognitive neuroscience link blunted emotion and moral transgression to overlapping deficits in prefrontal systems. This work identifies role of emotion in motivation morally-relevant action (Huebner et al., 2009).

9.7 Affiliation

Theorists have proposed that when coalitions are formed, a new "group mindedness" emerges, creating culture, institutions and social norms (Tomasello et al., 2012). A core feature that arises from group mindedness is the capacity for affiliation. Affiliation can be described as belonging to a social group that shares one's values, beliefs, or goals. The need to affiliate depends on trait level and situational factors. For example, in a classic study, Stanley Schachter showed that when a group of subjects are promised a large shock, compared to a group promised a low shock, they show a strong desire to be with others suggesting that emotional experiences of anxiety or fear promote the need to affiliate (Schachter, 1959). Further work by Sarnoff and Zimbardo suggested that fear increases affiliative behaviors while a reduction is observed in contexts that induce anxiety (Sarnoff & Zimbardo, 1961). Rofe argued that affiliation behavior depends critically on a predicted cost-benefit calculation, taking into account situational factors, individual traits, and the identity of others with which one may affiliate (Rofe, 1984). Together, these theories suggest that affiliation is closely tied with a psychological need for social support in certain contexts from certain people. More generally, affiliative tendencies may direct decision-making process to favor ingroup members, or particular characteristics valued by the individual's culture. For example, different cultural groups assign different value to specific attributes or characteristics, and these differences drive decision-making and behavior (Dolinsky & Stinerock, 1998). Culture also plays a role in emotional expression. For example, individualist cultures tend to value high arousal emotions (e.g., angry, excited) compared to valuing of low arousal emotions (e.g., relaxed, calm) in collectivist cultures (Lim, 2016). These cultural differences are reflected in the frequency with which individuals in different cultures report experiencing certain emotions, which has obvious implications for the way affective synchrony results in a feedback loop that sustains these cultural norms. Even when members are removed geographically from the region of origin, tightly bound cultures assign great importance to social traditions and tend to retain collectivist preferences. In such circumstances, evidence is accumulating that individuals originating from collectivist cultures that continue to adhere to the values espoused by that culture obtain better mental health outcomes (Bhugra et al., 2010).

9.7.1 Assimilation

According to Social Identity Theory, individuals have knowledge that they belong to a certain category of group and that self-concept is in part determined by the social group in which they belong (Hogg & Abrams, 1988; Tajfel & Turner, 1986). These extend from dialect, accent, and attire, where groups "police" their boundaries against out-group members by using "badges" for in-group membership. Individuals also engage in automatic mimicry which gives rise to emotional contagion, a form of affective assimilation (Prochazkova & Kret, 2017). A natural tendency towards imitation of in-group members is evident from an early age (Buttelmann et al., 2013) and most obvious in adolescence during which highly differentiated style and behavior are propagated by the group members attempting to find acceptance in the group. Fitting into the group is a complex process observed across cultures and socioeconomic status in adolescents trying to find their place in the world. Such ephemeral fashion changes also occur in language, including the appearance of new words and expressions to reflect the youth culture or sub-culture. These fashions are facilitated by skin color, geography, territory, and dialect with the common goal of showing that “I belong to this group”.

9.7.2 Belonging

Social belonging developed based on the importance of group membership as a critical force in survival during human evolutionary history, and is a powerful motivational factor in social behaviors, thoughts, and perception (Baumeister & Leary, 1995a). The need to belong is agnostic to culture, though individualist and collective cultures differ in terms of number and closeness of relationships (Verkuyten & Masson, 1996). Cultural differences in group goals have evolved significantly to encompass non-survival ends in modern contexts, however the basic social motivation of belonging continues to drive conformation of belief and behavior, and the consideration of others’ reactions in contemplating our own choices. The need to belong motivates the formation of attachment and interpersonal relationships that provide a sense of acceptance, and a reciprocal value relationship between the individual and group. Belonging provides and affirms a sense of identity, security, and self-worth, all of which contribute to the maintenance of positive affective equilibrium. Positive affect in turn has beneficial health consequences due to associations with protective psychosocial factors like social connectedness (Steptoe et al., 2009). Lambert et al. showed in a series of studies that belonging, more so than social support or social value, provides a greater sense of perceived meaningfulness of life (Lambert et al., 2013). An individual is willing to invest emotional and social capital into the group in the form of assistance and cooperation so long as the goals of others align with those of the individual, thus enhancing the meaning associated with participating in these activities. Ostracism from the group can result in seemingly counterintuitive self-preservation attempts to reduce the emotional distress that results from a potential loss of belonging (Woodyatt & Wenzel, 2013). The need to belong is so strong that in some cases individuals will signal group loyalty even when such signaling ignores certain acquisition of higher value for departing from the status quo. While superficially irrational, such behavior is socially motivated, consistent with a group identity, and hence perfectly rational under the social value construct**.** In order for social groups to function effectively, e.g. facilitate cooperation, trust must be established. Belonging and resulting social identity, together with a system of rewards and punishments, are the binding agents that hold group trust together. Emotions are one way the individual and the group determine who intends to abide by the social contract.

9.7.3 Allegiance and In-Group Favoritism

Allegiances work to bind the group, give it purpose, pride, solidarity, identity, and prestige. Allegiances can lead to greater commitment to the group and decreased desire to depart from the group even when it is disadvantageous to remain (Ellemers et al., 1997). Likewise, in-group favoritism can be seen as a primary means of reinforcing group solidarity and indeed represents one of the most well-demonstrated phenomena in social psychology. The ease and rapidity with which this group bias emerges is attested by a variety of research employing Tajfel's minimal group paradigm, in which subjects exhibit in-group favoritism despite knowledge that the relevant groups have been arbitrarily or randomly devised (M. Brewer, 1979; Diehl, 1990). Utilizing evidence from the minimal group paradigm, Tajfel and Turner (Tajfel & Turner, 1986) proposed that the individual's self-concept is shaped by the social group to which the individual believes they belong. In order to maintain a positive self-concept via their social identities, group members are thus motivated to arrive at favorable comparisons between their in-groups and salient out-groups. In-group members may arrive at conclusions motivated by directionality as opposed to accuracy and at the expense of being correct to signal loyalty. While seemingly maladaptive, this common behavior is rational from the context of reputational benefits that may be received within one's group. Some theorists, however, suggest that distinctly positive in-group evaluations are rooted not in socially-derived self-enhancement motives, but rather in the security and trust associated with in-group encounters, thus stressing a tie to mutualism (Brewer, 2007).

9.7.4 Selective Bonding

The maintenance and seeking of social bonds is one of the most powerful humans drives. We propose that bonding can be separated into several categories including attachment between the parent and the child, romantic love, or tight allegiances among a small group of friends. Bonding can be distinguished from belonging in that a need to belonging motivates bonding, but bonding as we define it is more selective and reciprocal.

1. ***Attachment.*** Selective bonding is most evident when examining the relationship between a mother and infant. Bowlby (Bowlby, 1988) maintained that attachment between the mother and infant is critical to healthy socialization. This is supported by the profound negative effects of maternal deprivation on non-

human primates (Harlow, 1958) and studies conducted on human children raised in orphanages (Bowlby, 1988; Telzer et al., 2013). Affective synchrony is an important feature of mother-child interactions, encompassing both the mother's and the child's responsivity and emotional capacity to flexibly respond to the other (Leclère et al., 2014). Synchrony in these bonded relationships differs from mirroring or the chameleon effect in part because it involves matching of emotional states. The ability to effectively respond in this crucial dyad has a myriad of implications for later development, including regulatory abilities, which can influence a child's later ability to engage in social groups outside of the family unit (Harrist & Waugh, 2002). Mother-infant bonds may be facilitated at the hormonal level by oxytocin, which has been found to increase during mother-infant bonding (Ross & Young, 2009). Further, the administration of an oxytocin agonist promotes maternal behaviour in virgin sheep (Kendrick, 2004), while an oxytocin antagonist inhibits such behaviour (van Leengoed et al., 1987). Along with candidate genes such as Grb10 (Garfield et al., 2011), OXTR (Pedersen et al., 2006), vasopressin, and the mu-opioid receptor gene OPRM1 (Moles et al., 2004), mother-infant bonding is presumably innate and critical to the healthy development and survival of offspring. Abnormal social development, including autism, has been proposed to be linked with atypical levels of oxytocin and vasopressin, the latter being linked with sensory processing (Carson et al., 2015). The capacity for normal social behaviors may develop and manifest due to a coordinated timing of signals in specific pathways, and begin with attachment to parents or caretakers.

2. ***Friendship and*** Social ***Networks.*** Enduring friendships are observed across a number of species including elephants, dolphins and chimpanzees (Seyfarth & Cheney, 2012). In humans, the formation of friendships is a common and highly adaptive social behavior. Baumeister and Leary (Baumeister & Leary, 1995a) propose that people seek out relationships at least to the point that satisfies an individual minimum threshold level of social contact and relationships, even in the absence of identifiable extrinsic incentives. Goals, achievements, and experiences are imbued with meaning when they can be witnessed and shared with others in one's social circle. Until the age of 12, friendships may be fleeting, yet individuals above this age tend to form long-term friendships and become emotionally close, even if they are physically distant (Selman, 1980; Selman & Schultz, 1990). Dunbar (Dunbar, 1993, 2010) has proposed a cognitive limit to the number of people with whom one can maintain stable relationships, which likely evolved when social groups were much smaller. Dunbar's number is placed at approximately 150 friends, around 15 of who are very close. Social structure features of modern societies are similar to those observed in Hunter-Gather societies (Apicella et al., 2012), suggesting that these structures may have evolved early in human history, perhaps during shared hunts and cooked meals (E. Wilson, 2012).
3. ***Romantic*** Love***.*** Love is arguably the strongest human bond between non-kin. When reciprocated, love floods the individual with ecstasy, while unrequited love may result in feelings of extreme sadness and despair (Hatfield & Rapson, 1993). Love elicits different emotions depending on the situation. Recognizing

and matching a romantic counterpart's emotional expression is, in part, what separates reciprocated and unrequited love. Brain imaging studies show that viewing images of a loved one results in increased activity in the brain reward and opioid systems (Aron et al., 2005), yet rejection by loved ones activates the brain pain systems (Kross et al., 2011). Individuals in romantic relationships demonstrate greater regulatory control during negative emotions (Song et al., 2016), which may be one mechanism underlying successful bonding. Romantic love begins in adolescence: approximately 25% of females begin dating by age 13, increasing to 75% by age 15 (Zimmer-Gembeck, 2002). In adults, love may result in longer-term commitment such as marriage, which sets rules on morally appropriate behaviour and is often tied to cultural and religious dogma.

9.8 Status Seeking

While status can be defined as an individual's group standing founded on honor, prestige and deference (Berger et al., 1972) others have defined it simply as respect and admiration (Leary et al., 2014) or superiority (Adler, 1930). No matter how we define it, there seems to be a human drive for high status (Anderson et al., 2015). One reason is that status has been perceived as a valuable resource, which yields direct utility to the individual (Huberman et al., 2004). In the Paleolithic period, status was given to tribe members with the best hunting skills as this was critical to the survival of the group (Ellis, 1993). Status objects such as jewelry soon evolved and go back 50,000 years acting as static markers of authority (Diamond, 1997). In modern contexts luxurious goods such as wristwatches and cars indicate high social status (Frank, 1999), and these are indicative of higher SES including financial wealth, education, and occupational prestige, yet may have no value other than to signal status. Affectively, pride is a major motivator for status-seeking (Cheng et al., 2010) and can signal status achievement through pride displays (e.g., posture, strutting). External displays of pride are likely innate given evidence that congenitally blind humans physically respond to success similar to sighted individuals (Tracy & Matsumoto, 2008). Notable differences exist in displays of failure among sighted and congenitally blind individuals suggesting sighted individuals may suppress low-status displays. Nonverbal expressions of pride are identified by young children (Tracy et al., 2005) across a range of cultures (Tracy & Robins, 2008), again supporting the assertion that status serves an important function in social groups.

9.8.1 Status as Social "Currency"

Social status has been proposed as a valuable resource yielding direct utility to the individual (Huberman et al., 2004). Some have noted that the drive to maintain a favorable image amongst peers, even strangers, may result in seemingly irrational and self-harmful choices, such as the sacrifice of tangible rewards. This phenomenon is referred to as “face-work” (Brown, 1968) and may extend to third-party instances in which people are even willing to incur a debt to acquire information about high-ranking individuals (e.g. celebrity gossip magazines). Interestingly, similar behaviors have been observed in rhesus macaques, who will sacrifice access to a palatable fluid in order to view images of high-status monkeys, yet require fluid overpayment in return for viewing low-status monkeys (Deaner et al., 2005). Evidence for the valuation of social status as a distinct “currency” in humans is further provided by investigations of the “winner’s curse”, or the tendency of individuals to bid more during auctions than prescribed by normative economic principles (van den Bos et al., 2008). For example, Delgado et al. (Delgado et al., 2008) have suggested that the social nature of auctions—specifically, the fear of losing in a social context—is a significant origin of overbidding practices. Rather than mere valuation anomalies, these findings may be understood in terms of a “common currency” that conveys social standing benefits as it does material ends. Indeed social standing may yield material benefits, and attract resources and loyalty if maintained and effectively signaled over time, discussed further below. Beyond tangible rewards, high-status may be intrinsically rewarding and is associated with increased dopamine receptor binding in humans (Martinez et al., 2010) and non-human primates (Morgan et al., 2002).

9.8.2 Status Signaling and Conspicuous Consumption

The drive to signal superiority is not a feature unique to humans but manifests across species, ranging from the display of the peacock’s tail and flashing of fireflies to the decorated recesses of the bowerbird and boisterous song of cicadas (Zehavi & Zahavi, 1997). According to sexual selection accounts, these elaborate displays confer a reproductive advantage by making apparent to the opposite sex favorable qualities (e.g. wealth, physical superiority) that boost the organism’s odds of being selected as a mate (Collins et al., 2015; De Fraja, 2009). Humans are no different. It has been suggested that charities commonly announce donors’ names in order to accommodate the reputation building strategies that are presumed to motivate contributions—termed “conspicuous compassion” (Engelmann & Fischbacher, 2009; West, 2004). Like otherwise costly reputation-building strategies which rely upon public consumption for their reward and evolution (Nowak, 2006; Tennie et al., 2010), high rank and prestige must be signaled to the group in order to derive the full benefits of their attainment. Highlighting this, the sociologist and economist Thorstein Veblen (Veblen, 1899) coined the term “conspicuous consumption” to refer to purchase behaviors driven principally by their ability to convey the owner’s status and prestige. Veblen’s notion was thus among the first to emphasize the social, rather than purely utilitarian, origins of consumer decision-making processes (Memushi, 2014). As Mason (Mason, 1984): “To the purely conspicuous consumer, the satisfaction derived from any particular purchase comes not from its value in use but from audience reaction to the wealth displayed by the purchaser in being able to secure the product for ‘consumption’” (p. 26). Beyond vast economic purchases and ostensible goods, social prestige may also be represented in the form of other culturally-attuned behaviors.

9.8.3 Value Seeking and Reputation Management

It has long been known by economists that consumption behaviors are driven by the social recognition or need to please one’s peers. Fiske also argues that the transfer of material “things” between people results in the highest-ranking individuals having more of better “things”. Indeed, Campbell-Meiklejohn and colleagues (Campbell-Meiklejohn et al., 2010) showed that the value of an object is determined by how others valued it. Humans are status maximizers and status is often acquired in complex ways. For example, people prefer to relay positive information (Rosen & Tesser, 1970) and weigh their advice more carefully when it reflects on them directly rather than through the medium of a third-party *(*Jonas et al., 2005*)*. One interpretation is that people like to yield information to others, particularly if it shines them in a positive light. Fitting with this idea, Anderson and Kildiff (Anderson & Kilduff, 2009) propose that status-seekers seek high status in an attempt to make themselves appear more important to the group, and this pursuit of values may be universal. Finally, behavioral and brain imaging work demonstrate that individuals report feeling more rewarded and show increased activity in the brain’s reward circuitry when observing others win money when winning is based on their advice compared to winning based on another’s advice (Mobbs et al., 2015). This supports a large body of research showing that reflected glory is a powerful form of social value seeking.

Studies across psychology and behavioral economics have long demonstrated that the individual’s actions are critically shaped by the mere presence of others. Often, such “audience effects” reflect the individual’s attempt to optimize their representation to fellow group members—a behavior referred to as reputation or impression management, and which has been delineated further in terms of separate motivation and construction components (Leary & Kowalski, 1990; Tennie et al., 2010). As Leary and Kowalski (1990) note, impression motivation and construction processes often operate outside the actor’s conscious awareness, thus stressing the deep-seated and automatic nature of the drive to project a favorable self-image to the group. Reputation-enhancing behaviors, such as charitable donations, have widely been shown to increase under conditions of social observation (Izuma et al., 2010) or even cues of observation (e.g. eyespots; (Haley & Fessler, 2005). Banerjee (Banerjee, 2002) has shown that self-representation behavior begins in children around the age of 8 years, while others suggest that this occurs much earlier. For example, 5- to 6-year-olds act more prosocially when they are observed or think they are being observed (J. M. Engelmann et al., 2012; Piazza et al., 2011). Similar findings have been observed in non-human animals—most notably the cleaner fish, which displays increased cooperative behavior with client fish when other watchful, or “image-scoring”, clients are present (Bshary & Grutter, 2006).

9.9 Competition

A key arena for status seeking is competition. Humphrey (Humphrey, 1976) proposes that primate cognition is due to social competition, which by definition includes a drive to perform better than others in the group. Likewise, Deutsch (Deutsch, 1949) suggested that in situations in which two or more people are attempting to attain a common goal in a zero sum environment, one agent will win as a result of the failure of others. Competition is a dominant ecological force in natural selection (Diamond, 1978) and evolutionary biologists typical explain competition through the lens of sexual selection and dominance hierarchies where organisms fight for leadership of the group. Social comparison is an important source of competitive behavior that influences self-perceptions via emotional reactions (Garcia et al., 2013).

9.10 Linking Drives to Group Living Success and Survival

The MASS drives proposed here are believed to facilitate group formation, stability, individual, and group success and map directly onto survival benefits (Fig. 9.1). While the MASS motives provide a general framework from which to explain behaviors that facilitate group living, we proposed that (1) mutualism increases shared goals, collaboration, and increases collective intelligence; (2) affiliation results in stronger group ties and identity and will facilitate in/out group competition. Furthermore, the stronger the affiliation, the more likely affiliates will protect you, share food, collaborate, share information, and provide social support; (3) status seeking enhances the likelihood that one would acquire the best mates, better protection from threat, provide first and access to information, and increased life quality and social support. It is also important to note that MASS motives do not work in isolation. For example, status seeking can be associated with increasing one's reputation as a good collaborator. A positive reputation and the benefits that obtain from maintaining such status may contribute to and increase mutualistic behaviors. The material and immaterial benefits (e.g. social support) that derive from cooperation reinforce such group behaviors resulting in greater probability of both individual and group survival. Affiliation through social bonds may also be the first step to allegiance and relate to both increases in status and mutualism.

Affective dynamics of reactive flexibility, affective synchrony, and emotional intelligence are proposed to facilitate attainment of MASS drives. These skills signal that one can provide benefit to the social group if included. The ability to respond to shifting social demands increases mutualism because of increased perceived trustworthiness (Slepian & Carr, 2019). Demonstrating emotional correspondence with social counterparts increases affiliation through intensification of group experiences (Páez et al., 2015). Competently regulating emotional experiences lays the foundation for status attainment through effective external displays (Shariff &

Tracy, 2009). Understanding how each MASS drive contributes to survival motivation can reveal distinct features of corresponding affective dynamics. For example, affective synchrony may facilitate affiliation but may undermine status-seeking.

The MASS model posits that a specific set of social behaviors facilitates a symbiotic arrangement at the local (interpersonal) and global (group) level and that shapes motivational processes to remain in the relationship given the psychological, material, survival, and other benefits that accrue due to the circular model. At the local level the costs incurred, typically time and effort to forge and maintain interpersonal relationships and perform functions in service of a group interest, will often yield a return that is both rewarding and meaningful to the individual. In some circumstances the rewards are not obvious or apparent, however when viewed at the global level, efforts may contribute to a pool of resources that serves as an emergent good for both the individual and group, e.g. collective intelligence, greater opportunities, optimization of skill application. Each of these increases the efficiency and flexibility of the species, thus imbuing a survival value to prosocial behavior.

9.11 Concluding Remarks

The human brain is wired for sociality, yet when investigating the social brain, researchers have focused on the cognitive operations rather than what drives sociality. Our theory proposes that the dynamics between MASS drives are founded on three chief premises: (1) living in groups provides fitness benefits; (2) these benefits have resulted in a set drives that need to be satisfied for successful group living; and (3) these drives are optimized by a set of evolved social behaviors, affective dynamics, and neurocognitive systems that facilitate group formation and enhance value and status in the group. With this theory, we can begin to unify social neuroscience with the related fields of anthropology, social psychology, affective science, sociology, and evolutionary biology. For example, MASS drives provide a universal account for why it is painful to be ostracized, why it is rewarding to be praised, why status is a driving force across many activities, why we feel the need to belong, why we conform, why we feel group pride, and why we experience out-group bias. Like any model, empirical predictions and falsifiability are required to adjudicate its usefulness. Our theory predicts that garnering other's respect should be rewarding, people should attempt to hide their weaknesses and promote their strengths, that people should act differently when interacting with higher or lower status individuals, and that the inability to optimize MASS drives will result in lower status, rejection, isolation, and, in turn, these hardships will lead to a significant reduction in access to all the benefits of group living. Cooperation and collaboration should yield group benefits that, when made available to all group members, improve individual wellbeing, and increase survivability. Many of these questions have already been tested, yet the burgeoning field of social psychology and social neuroscience will further clarify the value of social behavior.

References

Adler, A. (1930). *Social interest: A challenge to mankind (J. L. R. Vaughan, Trans.)*. Putnam.

Alexander, R. (1974). The evolution of social behavior. *Annual Review of Ecology and Systematics, 5*, 325–383.

Anderson, C., Hildreth, J. A., & Howland, L. (2015). Is the desire for status a fundamental human motive? A review of the empirical literature. *Psychological Bulletin, 141*(3), 574–601. https://doi.org/10.1037/a0038781

Anderson, C., & Kilduff, G. J. (2009). Why do dominant personalities attain influence in face-to-face groups? The competence-signaling effects of trait dominance. *Journal of Personality and Social Psychology, 96*(2), 491–503. https://doi.org/10.1037/a0014201

Anstey, M. L., Rogers, S. M., Ott, S. R., Burrows, M., & Simpson, S. J. (2009). Serotonin mediates behavioral gregarization underlying swarm formation in desert locusts. *Science, 323*(5914), 627–630. https://doi.org/10.1126/science.1165939

Apicella, C. L., Marlowe, F. W., Fowler, J. H., & Christakis, N. A. (2012). Social networks and cooperation in hunter-gatherers. *Nature, 481*(7382), 497–501. https://doi.org/10.1038/nature10736

Arnold, K., Owens, I., & Goldizen, A. (2005). Division of labour within cooperatively breeding groups. *Behaviour, 142*, 1577–1590.

Aron, A., Fisher, H., Mashek, D. J., Strong, G., Li, H., & Brown, L. L. (2005). Reward, motivation, and emotion systems associated with early-stage intense romantic love. *Journal of Neurophysiology, 94*(1), 327–337. https://doi.org/10.1152/jn.00838.2004

Bandura, A. (1962). Social learning through imitation. In Lincoln (Ed.), *Nebraska symposium on motivation*. University of Nebraska Press.

Banerjee, R. (2002). Audience effects on self-presentation in childhood. *Social Development, 11*, 487–507.

Barth, J., Schneider, S., & von Kanel, R. (2010). Lack of social support in the etiology and the prognosis of coronary heart disease: A systematic review and meta-analysis. *Psychosomatic Medicine, 72*(3), 229–238. https://doi.org/10.1097/PSY.0b013e3181d01611

Baumeister, R. F., & Leary, M. R. (1995a). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin, 117*(3), 497–529.

Baumeister, R. F., & Leary, M. R. (1995b). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin, 117*(3), 497–529. https://doi.org/10.1037/0033-2909.117.3.497

Berger, J., Cohen, B., & Zelditch, M. (1972). Status characteristics and social interaction. *American Sociological Review, 37*, 241–255.

Bhugra, D., Leff, J., Mallett, R., Morgan, C., & Zhao, J. H. (2010). The culture and identity schedule a measure of cultural affiliation: Acculturation, marginalization and schizophrenia. *The International Journal of Social Psychiatry, 56*(5), 540–556. https://doi.org/10.1177/0020764009358024

Blair, B. L., Perry, N. B., O'Brien, M., Calkins, S. D., Keane, S. P., & Shanahan, L. (2015). Identifying developmental cascades among differentiated dimensions of social competence and emotion regulation. *Developmental Psychology, 51*(8), 1062–1073. https://doi.org/10.1037/a0039472

Blue, P. R., Hu, J., Lu, P., Yu, H., Liu, H., & Zhou, X. (2020). Whose promises are worth more? How social status affects trust in promises. *European Journal of Social Psychology, 50*(1), 189–206. https://doi.org/10.1002/ejsp.2596

Bonanno, G. A., & Burton, C. L. (2013). Regulatory flexibility: An individual differences perspective on coping and emotion regulation. *Perspectives on Psychological Science, 8*(6), 591–612. https://doi.org/10.1177/1745691613504116

Bowlby, J. (1988). *A secure base: Clinical applications of attachment theory*. Routledge.

Brewer, M. (1979). In-group bias in the minimal intergroup situation: A cognitive-motivational analysis. *Psychological Bulletin, 86*, 307–324.

Brewer, M. B. (2007). The importance of being we: Human nature and intergroup relations. *The American Psychologist, 62*(8), 726–738. https://doi.org/10.1037/0003-066X.62.8.728

Brown, B. (1968). The effects of need to maintain face on interpersonal bargaining. *Journal of Experimental Social Psychology, 4*, 107–122.

Bshary, R., & Grutter, A. S. (2006). Image scoring and cooperation in a cleaner fish mutualism. *Nature, 441*(7096), 975–978. https://doi.org/10.1038/nature04755

Buttelmann, D., Zmyj, N., Daum, M., & Carpenter, M. (2013). Selective imitation of in-group over out-group members in 14-month-old infants. *Child Development, 84*(2), 422–428. https://doi.org/10.1111/j.1467-8624.2012.01860.x

Campbell-Meiklejohn, D. K., Bach, D. R., Roepstorff, A., Dolan, R. J., & Frith, C. D. (2010). How the opinion of others affects our valuation of objects. *Current Biology, 20*(13), 1165–1170. https://doi.org/10.1016/j.cub.2010.04.055

Carlisle, D., & Ellis, P. (1963). Prothoracid gland and gregarious behavior in locusts. *Nature, 200*, 603–604.

Carson, D. S., Garner, J. P., Hyde, S. A., Libove, R. A., Berquist, S. W., Hornbeak, K. B., et al. (2015). Arginine vasopressin is a blood-based biomarker of social functioning in children with autism. *PLoS One, 10*(7), e0132224. https://doi.org/10.1371/journal.pone.0132224

Castiello, U., Becchio, C., Zoia, S., Nelini, C., Sartori, L., Blason, L., et al. (2010). Wired to be social: The ontogeny of human interaction. *PLoS One, 5*(10), e13199. https://doi.org/10.1371/journal.pone.0013199

Cheng, J. T., Tracy, J. L., & Henrich, J. (2010). Pride, personality, and the evolutionary foundations of human social status. *Evolution and Human Behavior, 31*(5), 334–347. https://doi.org/10.1016/j.evolhumbehav.2010.02.004

Clutton-Brock, T. (2002). Breeding together: Kin selection and mutualism in cooperative vertebrates. *Science, 296*(5565), 69–72. https://doi.org/10.1126/science.296.5565.69

Cohen, S., Doyle, W. J., Skoner, D. P., Rabin, B. S., & Gwaltney, J. M., Jr. (1997). Social ties and susceptibility to the common cold. *JAMA, 277*(24), 1940–1944.

Collins, J., Baer, B., & Weber, E. (2015). Sexual selection, conspicuous consumption and economic growth. *Journal of Bioeconomics, 17*, 189–206.

Cottrell, C. A., & Neuberg, S. L. (2005). Different emotional reactions to different groups: A sociofunctional threat-based approach to ‘prejudice. *Journal of Personality and Social Psychology, 88*(5), 770–789. https://doi.org/10.1037/0022-3514.88.5.770

Crockett, M. J. (2013). Models of morality. *Trends in Cognitive Sciences, 17*(8), 363–366. https://doi.org/10.1016/j.tics.2013.06.005

Cushman, F. (2013). Action, outcome, and value: A dual-system framework for morality. *Personality and Social Psychology Review, 17*(3), 273–292. https://doi.org/10.1177/1088868313495594

De Fraja, G. (2009). The origin of utility: Sexual selection and conspicuous consumption. *Journal of Economic Behavior & Organization, 72*, 51–69.

de Waal, F. (2011). What is an animal emotion? *Annals of the New York Academy of Sciences, 1224*, 191–206.

Deaner, R. O., Khera, A. V., & Platt, M. L. (2005). Monkeys pay per view: Adaptive valuation of social images by rhesus macaques. *Current Biology, 15*(6), 543–548. https://doi.org/10.1016/j.cub.2005.01.044

Decety, J., Bartal, I. B.-A., Uzefovsky, F., & Knafo-Noam, A. (2016). Empathy as a driver of prosocial behaviour: Highly conserved neurobehavioural mechanisms across species. *Philosophical Transactions of the Royal Society B: Biological Sciences, 371*(1686). https://doi.org/10.1098/rstb.2015.0077

Deci, E., & Ryan, R. (2008). Self-Determination theory: A macrotheory of human motivation, development, and health. *Canadian Psychology, 49*, 182–185.

Delgado, M. R., Schotter, A., Ozbay, E. Y., & Phelps, E. A. (2008). Understanding overbidding: Using the neural circuitry of reward to design economic auctions. *Science, 321*(5897), 1849–1852. https://doi.org/10.1126/science.1158860

Deutsch, M. (1949). A theory of co-operation and competition. *Human Relations, 2*, 129–152.

Diamond, J. (1978). Niche shifts and the rediscovery of interspecific competition. *American Scientist, 66*, 322–331.

Diamond, J. (1997). *Guns, germs and steel: The fates of human societies*. W.W. Norton & Company.

Diehl, M. (1990). The minimal group paradigm: Theoretical explanations and empirical findings. *European Review of Social Psychology, 1*, 263–292.

Dolinsky, A. L., & Stinerock, R. (1998). Cultural affiliation and the importance of health care attributes. Marketers can develop segmentation strategies for targeted patient groups. *Marketing Health Services, 18*(1), 28–37.

Dunbar, R. (1993). Coevolution of neocortical size, group size and language in humans. *Behavioral and Brain Sciences, 16*, 681–735.

Dunbar, R. I. M. (2010). *How many friends does one person need?: Dunbar's number and other evolutionary quirks*. Harvard University Press.

Eisenberger, N. I., & Cole, S. W. (2012). Social neuroscience and health: Neurophysiological mechanisms linking social ties with physical health. *Nature Neuroscience, 15*(5), 669–674. https://doi.org/10.1038/nn.3086

Ellemers, N., Spears, R., & Doosje, B. (1997). Sticking together or falling apart: In-group identification as a psychological determinant of group commitment versus individual mobility. *Journal of Personality and Social Psychology, 72*, 617–626.

Ellis, L. (1993). *Social stratification and socioeconomic inequality*. Praeger.

Engelmann, D., & Fischbacher, U. (2009). Indirect reciprocity and strategic reputation building in an experimental helping game. *Games and Economic Behavior, 67*, 399–407.

Engelmann, J. M., Herrmann, E., & Tomasello, M. (2012). Five-year olds, but not chimpanzees, attempt to manage their reputations. *PLoS One, 7*(10), e48433. https://doi.org/10.1371/journal.pone.0048433

Fehr, E., Bernhard, H., & Rockenbach, B. (2008). Egalitarianism in young children. *Nature, 454*(7208), 1079–1083. https://doi.org/10.1038/nature07155

Fehr, E., & Fischbacher, U. (2003). The nature of human altruism. *Nature, 425*(6960), 785–791. https://doi.org/10.1038/nature02043

Fehr, E., & Gachter, S. (2002). Altruistic punishment in humans. *Nature, 415*(6868), 137–140. https://doi.org/10.1038/415137a

Feldman Hall, O., & Mobbs, D. (2015). A neural network for moral decision making. In A. W. Toga (Ed.), *Brain mapping: An encyclopedic reference* (pp. 205–210). Academic.

Fiske, S. (2002). Five core social motives, plus or minus five. In S. F. S. J. Spencer, M. P. Zanna, & J. Olsen (Eds.), *Motivated social perception: The Ontario Symposium* (pp. 233–246). Erlbaum.

Foster, W., & Treherne, J. (1981). Evidence for the dilution effect in the selfish herd from fish predation on a marine insect. *Nature, 293*, 466–467.

Frank, R. H. (1999). *Luxury fever: Why money fails to satisfy in an era of excess*. The Free Press.

Galton, F. (1907). The wisdom of crowds. *Nature, 75*, 450–451.

Garcia, S. M., Tor, A., & Schiff, T. M. (2013). The psychology of competition: A social comparison perspective. *Perspectives on Psychological Science.* https://doi.org/10.1177/1745691613504114

Garfield, A., Cowley, M., Smith, F., Moorwood, K., Stewart-Cox, J., Gilroy, K., et al. (2011). Distinct physiological and behavioural functions for parental alleles of imprinted Grb10. *Nature, 469*, 534–538.

Gilam, G., Abend, R., Shani, H., Ben-Zion, Z., & Hendler, T. (2019). The anger-infused ultimatum game: A reliable and valid paradigm to induce and assess anger. *Emotion, 19*(1), 84–96. https://doi.org/10.1037/emo0000435

Gilbert, D. T., Killingsworth, M. A., Eyre, R. N., & Wilson, T. D. (2009). The surprising power of neighborly advice. *Science, 323*(5921), 1617–1619. https://doi.org/10.1126/science.1166632

Giraldeau, L. (1984). Group foraging: The skill pool effect and frequency-dependent learning. *The American Naturalist, 124*, 72–79.

Granic, I., O'Hara, A., Pepler, D., & Lewis, M. D. (2007). A Dynamic Systems Analysis of Parent-Child Changes Associated with Successful 'Real-World' Interventions for Aggressive

Children. *Journal of Abnormal Child Psychology, 35*(5), 845–857. https://doi.org/10.1007/s10802-007-9133-4

Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological Inquiry, 26*(1), 1–26. https://doi.org/10.1080/1047840X.2014.940781

Gurven, M. (2004). Reciprocal altruism and food sharing decisions among Hiwi and Ache hunter-gatherers. *Behavioral Ecology and Sociobiology, 56*, 366–380.

Guth, W., Schmittberger, R., & Schwarze, B. (1982). An experimental analysis of ultimatum bargaining. *Journal of Economic Behavior & Organization, 3*, 367–388.

Haldane, J. B. S. (1932). *The causes of evolution*. Longmans, Green and Co..

Haley, K., & Fessler, D. (2005). Nobody's watching? Subtle cues affect generosity in an anonymous economic game. *Evolution and Human Behavior, 26*, 245–256.

Harlow, H. F. (1958). The nature of love. *American Psychologist, 13*, 673–685.

Harrist, A. W., & Waugh, R. M. (2002). Dyadic synchrony: Its structure and function in children's development. *Developmental Review, 22*(4), 555–592. https://doi.org/10.1016/S0273-2297(02)00500-2

Hatfield, E., & Rapson, R. (1993). Love and attachment processes. In M. L. J. Haviland (Ed.), *Handbook of emotions*. Guilford Press.

Heerdink, M. W., Koning, L. F., van Doorn, E. A., & van Kleef, G. A. (2019). Emotions as guardians of group norms: Expressions of anger and disgust drive inferences about autonomy and purity violations. *Cognition and Emotion, 33*(3), 563–578. https://doi.org/10.1080/02699931.2018.1476324

Henke, J. M., & Bassler, B. L. (2004). Bacterial social engagements. *Trends in Cell Biology, 14*(11), 648–656. https://doi.org/10.1016/j.tcb.2004.09.012

Hepach, R., Vaish, A., & Tomasello, M. (2012). Young children are intrinsically motivated to see others helped. *Psychological Science, 23*(9), 967–972. https://doi.org/10.1177/0956797612440571

Hogg, M. A., & Abrams, D. (1988). *Social identifications: A social psychology of intergroup relations and group processes*. Routledge.

Hollenstein, T. (2015). This time, it's real: Affective flexibility, time scales, feedback loops, and the regulation of emotion. *Emotion Review, 7*(4), 308–315. https://doi.org/10.1177/1754073915590621

Huberman, B., Loch, C., & Onculer, A. (2004). Status as a valued resource. *Social Psychology Quarterly, 67*, 103–114.

Huebner, B., Dwyer, S., & Hauser, M. (2009). The role of emotion in moral psychology. *Trends in Cognitive Sciences, 13*(1), 1–6. https://doi.org/10.1016/j.tics.2008.09.006

Humphrey, N. (1976). The social function of intellect. In P. P. G. B. A. R. A. Hinde (Ed.), *Growing points in ethology* (pp. 303–317). Cambridge University Press.

Hyon, R., Kleinbaum, A. M., & Parkinson, C. (2020). Social network proximity predicts similar trajectories of psychological states: Evidence from multi-voxel spatiotemporal dynamics. *NeuroImage, 216*, 116492. https://doi.org/10.1016/j.neuroimage.2019.116492

Izuma, K., Saito, D. N., & Sadato, N. (2010). Processing of the incentive for social approval in the ventral striatum during charitable donation. *Journal of Cognitive Neuroscience, 22*(4), 621–631. https://doi.org/10.1162/jocn.2009.21228

Jonas, E., Schulz-Hardt, S., & Frey, D. (2005). Giving advice or making decisions in someone else's place: The influence of impression, defense, and accuracy motivation on the search for new information. *Personality and Social Psychology Bulletin, 31*(7), 977–990. https://doi.org/10.1177/0146167204274095

Jordan, J. J., Hoffman, M., Bloom, P., & Rand, D. G. (2016a). Third-party punishment as a costly signal of trustworthiness. *Nature, 530*(7591), 473–476. https://doi.org/10.1038/nature16981

Kappes, A., Kahane, G., & Crockett, M. J. (2016). From risk to fairness. *Proceedings of the National Academy of Sciences of the United States of America, 113*(42), 11651–11653. https://doi.org/10.1073/pnas.1614111113

Kendrick, K. M. (2004). The neurobiology of social bonds. *Journal of Neuroendocrinology, 16*(12), 1007–1008. https://doi.org/10.1111/1365-2826.2004.01262.x

Krebs, J. (1972). Flocking and feeding in the great tit Parus major: An experimental study. *Ibis, 114*, 507–530.

Krebs, J., & Davies, N. (1997). *Behavioral ecology: An evolutionary approach*. Wiley-Blackwell.

Kross, E., Berman, M. G., Mischel, W., Smith, E. E., & Wager, T. D. (2011). Social rejection shares somatosensory representations with physical pain. *Proceedings of the National Academy of Sciences of the United States of America, 108*(15), 6270–6275. https://doi.org/10.1073/pnas.1102693108

Lambert, N. M., Stillman, T. F., Hicks, J. A., Kamble, S., Baumeister, R. F., & Fincham, F. D. (2013). To belong is to matter: Sense of belonging enhances meaning in life. *Personality and Social Psychology Bulletin, 39*(11), 1418–1427. https://doi.org/10.1177/0146167213499186

Lawler, E. J. (2001). An affect theory of social exchange. *American Journal of Sociology, 107*(2), 321–352. https://doi.org/10.1086/324071

Leary, M. R., Jongman-Sereno, K., & Diebels, K. (2014). The pursuit of status: A self-presentational perspective on the quest for social value. In J. Cheng, J. Tracy, & C. Anderson (Eds.), *The psychology of social status*. Springer.

Leary, M. R., & Kowalski, R. (1990). Impression management: A literature review and two-component model. *Psychological Bulletin, 107*, 34–47.

Leclère, C., Viaux, S., Avril, M., Achard, C., Chetouani, M., Missonnier, S., & Cohen, D. (2014). Why synchrony matters during mother-child interactions: A systematic review. *PLoS One, 9*(12). https://doi.org/10.1371/journal.pone.0113571

LeDoux, J. E. (2012). Evolution of human emotion. *Progress in Brain Research, 195*, 431–442. https://doi.org/10.1016/B978-0-444-53860-4.00021-0

Lee, T.-H., Miernicki, M. E., & Telzer, E. H. (2017). Families that fire together smile together: Resting state connectome similarity and daily emotional synchrony in parent-child dyads. *NeuroImage, 152*, 31–37. https://doi.org/10.1016/j.neuroimage.2017.02.078

Lim, N. (2016). Cultural differences in emotion: Differences in emotional arousal level between the east and the west. *Integrative Medicine Research, 5*(2), 105–109. https://doi.org/10.1016/j.imr.2016.03.004

Livnat, A., Papadimitriou, C., Dushoff, J., & Feldman, M. W. (2008). A mixability theory for the role of sex in evolution. *Proceedings of the National Academy of Sciences of the United States of America, 105*(50), 19803–19808. https://doi.org/10.1073/pnas.0803596105

Loucks, E. B., Sullivan, L. M., D'Agostino, R. B., Sr., Larson, M. G., Berkman, L. F., & Benjamin, E. J. (2006). Social networks and inflammatory markers in the Framingham Heart Study. *Journal of Biosocial Science, 38*(6), 835–842. https://doi.org/10.1017/S0021932005001203

Martinez, D., Orlowska, D., Narendran, R., Slifstein, M., Liu, F., Kumar, D., Broft, A., Van Heertum, R., & Kleber, H. D. (2010). Dopamine type 2/3 receptor availability in the striatum and social status in human volunteers. *Biological Psychiatry, 67*(3), 275–278. https://doi.org/10.1016/j.biopsych.2009.07.037

Maslow, A. (1943). A theory of human motivation. *Psychological Review, 50*, 370–396.

Mason, R. (1984). Conspicuous consumption: A literature review. *European Journal of Marketing, 18*, 26–39.

McClelland, D. C. (1965). Toward a theory of motive acquisition. *The American Psychologist, 20*, 321–333.

McNamara, J. M., Stephens, P. A., Dall, S. R., & Houston, A. I. (2009). Evolution of trust and trustworthiness: Social awareness favours personality differences. *Proceedings of the Biological Sciences, 276*(1657), 605–613. https://doi.org/10.1098/rspb.2008.1182

Memushi, A. (2014). Conspicuous consumption and Albanians: Determinant factors. *South-Eastern Europe Journal of Economics, 1*, 65–87.

Mobbs, D. (2018). The ethological deconstruction of fear(s). *Current Opinion in Behavioral Sciences, 24*, 32–37.

Mobbs, D., Hagan, C. C., Yu, R., Takahashi, H., FeldmanHall, O., Calder, A. J., & Dalgleish, T. (2015). Reflected glory and failure: The role of the medial prefrontal cortex and ventral striatum in self vs other relevance during advice-giving outcomes. *Social Cognitive and Affective Neuroscience, 10*(10), 1323–1328. https://doi.org/10.1093/scan/nsv020

Moles, A., Kieffer, B. L., & D'Amato, F. R. (2004). Deficit in attachment behavior in mice lacking the mu-opioid receptor gene. *Science, 304*(5679), 1983–1986. https://doi.org/10.1126/science.1095943

Moll, H., & Tomasello, M. (2007). Cooperation and human cognition: The Vygotskian intelligence hypothesis. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences, 362*(1480), 639–648. https://doi.org/10.1098/rstb.2006.2000

Morgan, D., Ka, G., Hd, G., Mach, R., Jr, K., Prioleau, O., Nader, S., Buchheimer, N., Rl, E., & Ma, N. (2002). Social dominance in monkeys: Dopamine d2 receptors and cocaine self-administration. *Nature Neuroscience, 5*(2). Retrieved December 1, 2020, from https://pubmed.ncbi.nlm.nih.gov/11802171/

Nonacs, P., & Kapheim, K. M. (2007). Social heterosis and the maintenance of genetic diversity. *Journal of Evolutionary Biology, 20*(6), 2253–2265. https://doi.org/10.1111/j.1420-9101.2007.01418.x

Nowak, M. A. (2006). Five rules for the evolution of cooperation. *Science, 314*(5805), 1560–1563. https://doi.org/10.1126/science.1133755

Oatley, K., & Johnson-laird, P. N. (1987). Towards a cognitive theory of emotions. *Cognition and Emotion, 1*(1), 29–50. https://doi.org/10.1080/02699938708408362

Onishi, K. H., & Baillargeon, R. (2005). Do 15-month-old infants understand false beliefs? *Science, 308*(5719), 255–258. https://doi.org/10.1126/science.1107621

Oosterhof, N. N., & Todorov, A. (2009). Shared perceptual basis of emotional expressions and trustworthiness impressions from faces. *Emotion, 9*(1), 128–133. https://doi.org/10.1037/a0014520

Páez, D., Rimé, B., Basabe, N., Wlodarczyk, A., & Zumeta, L. (2015). Psychosocial effects of perceived emotional synchrony in collective gatherings. *Journal of Personality and Social Psychology, 108*(5), 711–729. https://doi.org/10.1037/pspi0000014

Pedersen, C. A., Vadlamudi, S. V., Boccia, M. L., & Amico, J. A. (2006). Maternal behavior deficits in nulliparous oxytocin knockout mice. *Genes, Brain, and Behavior, 5*(3), 274–281. https://doi.org/10.1111/j.1601-183X.2005.00162.x

Piazza, J., Bering, J. M., & Ingram, G. (2011). "Princess Alice is watching you": Children's belief in an invisible person inhibits cheating. *Journal of Experimental Child Psychology, 109*(3), 311–320. https://doi.org/10.1016/j.jecp.2011.02.003

Prochazkova, E., & Kret, M. E. (2017). Connecting minds and sharing emotions through mimicry: A neurocognitive model of emotional contagion. *Neuroscience & Biobehavioral Reviews, 80*, 99–114. https://doi.org/10.1016/j.neubiorev.2017.05.013

Pruetz, J. D., & Lindshield, S. (2012). Plant-food and tool transfer among savanna chimpanzees at Fongoli, Senegal. *Primates, 53*(2), 133–145. https://doi.org/10.1007/s10329-011-0287-x

Reeve, J. (2014). *Understanding motivation and emotion*. John Wiley & Sons.

Rofe, Y. (1984). Stress and affiliation: A utility theory. *Psychological Review, 91*, 235–250.

Rosen, S., & Tesser, A. (1970). On reluctance to communicate undesirable information: The MUM effect. *Sociometry, 33*, 253–263.

Ross, H. E., & Young, L. J. (2009). Oxytocin and the neural mechanisms regulating social cognition and affiliative behavior. *Frontiers in Neuroendocrinology, 30*(4), 534–547. https://doi.org/10.1016/j.yfrne.2009.05.004

Rule, N. O., Krendl, A. C., Ivcevic, Z., & Ambady, N. (2013). Accuracy and consensus in judgments of trustworthiness from faces: Behavioral and neural correlates. *Journal of Personality and Social Psychology, 104*(3), 409–426. https://doi.org/10.1037/a0031050

Sarnoff, I., & Zimbardo, P. G. (1961). Anxiety, fear, and social affiliation. *Journal of Abnormal and Social Psychology, 62*, 356–363.

Schachter, S. (1959). *The psychology of affiliation*. Stanford University Press.

Schmidt, M. F., & Sommerville, J. A. (2011). Fairness expectations and altruistic sharing in 15-month-old human infants. *PLoS One, 6*(10), e23223. https://doi.org/10.1371/journal.pone.0023223

Schwarz, N., & Clore, G. L. (1983). Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. *Journal of Personality and Social Psychology, 45*(3), 513–523. https://doi.org/10.1037/0022-3514.45.3.513

Seeman, T. E., & McEwen, B. S. (1996). Impact of social environment characteristics on neuroendocrine regulation. *Psychosomatic Medicine, 58*(5), 459–471.

Selman, R. L. (1980). *The growth of interpersonal understanding: Developmental and clinical analyses*. Academic.

Selman, R. L., & Schultz, L. H. (1990). *Making a friend in youth: Developmental theory and pair therapy*. University of Chicago Press.

Seyfarth, R. M., & Cheney, D. L. (2012). The evolutionary origins of friendship. *Annual Review of Psychology, 63*, 153–177. https://doi.org/10.1146/annurev-psych-120710-100337

Shariff, A. F., & Tracy, J. L. (2009). Knowing who's boss: Implicit perceptions of status from the nonverbal expression of pride. *Emotion, 9*(5), 631–639. https://doi.org/10.1037/a0017089

Shultz, S., Opie, C., & Atkinson, Q. D. (2011). Stepwise evolution of stable sociality in primates. *Nature, 479*(7372), 219–222. https://doi.org/10.1038/nature10601

Silk, J. B. (2007). The adaptive value of sociality in mammalian groups. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences, 362*(1480), 539–559. https://doi.org/10.1098/rstb.2006.1994

Singer, T., Seymour, B., O'Doherty, J. P., Stephan, K. E., Dolan, R. J., & Frith, C. D. (2006). Empathic neural responses are modulated by the perceived fairness of others. *Nature, 439*(7075), 466–469. https://doi.org/10.1038/nature04271

Slepian, M. L., & Carr, E. W. (2019). Facial expressions of authenticity: Emotion variability increases judgments of trustworthiness and leadership. *Cognition, 183*, 82–98. https://doi.org/10.1016/j.cognition.2018.10.009

Song, S., Zou, Z., Song, H., Wang, Y., d'Oleire Uquillas, F., Wang, H., & Chen, H. (2016). Romantic love is associated with enhanced inhibitory control in an emotional stop-signal task. *Frontiers in Psychology, 7*. https://doi.org/10.3389/fpsyg.2016.01574

Steptoe, A., Shankar, A., Demakakos, P., & Wardle, J. (2013). Social isolation, loneliness, and all-cause mortality in older men and women. *Proceedings of the National Academy of Sciences of the United States of America, 110*(15), 5797–5801. https://doi.org/10.1073/pnas.1219686110

Steptoe, A., Dockray, S., & Wardle, J. (2009). Positive affect and psychobiological processes relevant to health. *Journal of Personality, 77*(6), 1747–1776. https://doi.org/10.1111/j.1467-6494.2009.00599.x

Surowiecki, J. (2004). *The wisdom of crowds*. W.W. Norton & Company.

Svetlova, M., Nichols, S. R., & Brownell, C. A. (2010). Toddlers' prosocial behavior: From instrumental to empathic to altruistic helping. *Child Development, 81*(6), 1814–1827. https://doi.org/10.1111/j.1467-8624.2010.01512.x

Tajfel, H., & Turner, J. (1986). The social identity theory of intergroup behaviour. In S. W. W. G. Austin (Ed.), *Psychology of intergroup relations*. Nelson-Hall.

Talhelm, T., Zhang, X., Oishi, S., Shimin, C., Duan, D., Lan, X., & Kitayama, S. (2014). Large-scale psychological differences within China explained by rice versus wheat agriculture. *Science, 344*(6184), 603–608. https://doi.org/10.1126/science.1246850

Telzer, E. H., Flannery, J., Shapiro, M., Humphreys, K. L., Goff, B., Gabard-Durman, L., et al. (2013). Early experience shapes amygdala sensitivity to race: An international adoption design. *The Journal of Neuroscience, 33*(33), 13484–13488. https://doi.org/10.1523/JNEUROSCI.1272-13.2013

Tennie, C., Frith, U., & Frith, C. D. (2010). Reputation management in the age of the world-wide web. *Trends in Cognitive Sciences, 14*(11), 482–488. https://doi.org/10.1016/j.tics.2010.07.003

Terborgh, J., & Janson, C. (1986). The socioecology of primate groups. *Annual Review of Ecology and Systematics, 17*, 111–136.

Todd, R. M., Cunningham, W. A., Anderson, A. K., & Thompson, E. (2012). Affect-biased attention as emotion regulation. *Trends in Cognitive Sciences, 16*(7), 365–372. https://doi.org/10.1016/j.tics.2012.06.003

Tolman, E. (1932). *Purposive behavior in animals and men*. The Century.

Tomasello, M., Carpenter, M., Call, J., Behne, T., & Moll, H. (2005). Understanding and sharing intentions: The origins of cultural cognition. *The Behavioral and Brain Sciences, 28*(5), 675–691.; ; discussion 691–735. https://doi.org/10.1017/S0140525X05000129

Tomasello, M., Melis, A., Tennie, C., Wyman, E., & Herrmann, E. (2012). Two key steps in the evolution of human cooperation: The interdependence hypothesis. *Current Anthropology, 53*, 673–692.

Torres, V. O., Montagna, T. S., Raizer, J., & Antonialli-Junior, W. F. (2012). Division of labor in colonies of the eusocial wasp, Mischocyttarus consimilis. *Journal of Insect Science, 12*, 21. https://doi.org/10.1673/031.012.2101

Tracy, J. L., & Matsumoto, D. (2008). The spontaneous expression of pride and shame: Evidence for biologically innate nonverbal displays. *Proceedings of the National Academy of Sciences, 105*(33), 11655–11660. https://doi.org/10.1073/pnas.0802686105

Tracy, J. L., & Robins, R. W. (2008). The nonverbal expression of pride: Evidence for cross-cultural recognition. *Journal of Personality and Social Psychology, 94*(3), 516–530. https://doi.org/10.1037/0022-3514.94.3.516

Tracy, J. L., Robins, R. W., & Lagattuta, K. H. (2005). Can children recognize pride? *Emotion (Washington, D.C.), 5*(3), 251–257. https://doi.org/10.1037/1528-3542.5.3.251

Valenza, E., Simion, F., Cassia, V. M., & Umilta, C. (1996). Face preference at birth. *Journal of Experimental Psychology. Human Perception and Performance, 22*(4), 892–903.

Van Bavel, J., Feldman Hall, O., & Mende-Siedlecki, P. (2015). The neuroscience of moral cognition: From dual process to dynamic systems. *Current Opinion in Psychology, 6*, 167–172.

van den Bos, W., Li, J., Lau, T., Maskin, E., Cohen, J., & McClure, S. (2008). The value of victory, social origins of the winner's curse in common value auctions. *Judgment and Decision making, 3*, 483–492.

van Kleef, G. A., Cheshin, A., Fischer, A. H., & Schneider, I. K. (2016). Editorial: The social nature of emotions. *Frontiers in Psychology, 7*. https://doi.org/10.3389/fpsyg.2016.00896

van Leengoed, E., Kerker, E., & Swanson, H. (1987). Inhibition of post-partum maternal behaviour in the rat by injecting an oxytocin antagonist into the cerebral ventricles. *Journal of Endocrinology, 112*, 275–282.

Vanutelli, M. E., Gatti, L., Angioletti, L., & Balconi, M. (2017). Affective synchrony and autonomic coupling during cooperation: A hyperscanning study. *BioMed Research International, 2017*, e3104564. Retrieved November 10, 2020, from https://www.hindawi.com/journals/bmri/2017/3104564/

Veblen, T. (1899). The theory of the leisure class; an economic study in the evolution of institutions. ,

Verkuyten, M., & Masson, K. (1996). Culture and gender differences in the perception of friendship by adolescents. *International Journal of Psychology, 31*, 207–217.

Warneken, F., & Tomasello, M. (2009). The roots of human altruism. *British Journal of Psychology, 100*(Pt 3), 455–471. https://doi.org/10.1348/000712608X379061

Wegner, D. M., Erber, R., & Raymond, P. (1991). Transactive memory in close relationships. *Journal of Personality and Social Psychology, 61*(6), 923–929.

West, P. (2004). *Conspicuous compassion: Why sometimes it really is cruel to be kind*. Civitas.

West, S. A., Griffin, A. S., & Gardner, A. (2007). Social semantics: Altruism, cooperation, mutualism, strong reciprocity and group selection. *Journal of Evolutionary Biology, 20*(2), 415–432. https://doi.org/10.1111/j.1420-9101.2006.01258.x

Wilson, D. S., & Wilson, E. O. (2007). Rethinking the theoretical foundation of sociobiology. *The Quarterly Review of Biology, 82*(4), 327–348.

Wilson, E. (2012). *The social conquest of earth*. W.W. Norton &.

Wood, A., Rychlowska, M., Korb, S., & Niedenthal, P. (2016). Fashioning the Face: Sensorimotor Simulation Contributes to Facial Expression Recognition. *Trends in Cognitive Sciences, 20*(3), 227–240. https://doi.org/10.1016/j.tics.2015.12.010

Woodyatt, L., & Wenzel, M. (2013). The psychological immune response in the face of transgressions: Pseudo self-forgiveness and threat to belonging. *Journal of Experimental Social Psychology, 49*(6), 951–958. https://doi.org/10.1016/j.jesp.2013.05.016

Yu, R., Calder, A. J., & Mobbs, D. (2014). Overlapping and distinct representations of advantageous and disadvantageous inequality. *Human Brain Mapping, 35*(7), 3290–3301.

Zehavi, A., & Zahavi, A. (1997). *The handicap principle: A missing piece of Darwin's puzzle*. Oxford University Press.

Zimmer-Gembeck, M. J. (2002). The development of romantic relationships and adaptations in the system of peer relationships. *The Journal of Adolescent Health, 31*(6 Suppl), 216–225.

Part IV
Computational Models of Affect

Chapter 10
Computational Models for Affect Dynamics

Niels Vanhasbroeck , Sigert Ariens , Francis Tuerlinckx, and Tim Loossens

Abstract Computational models of affect dynamics are ubiquitous. These models are appropriate for either exploring intensive longitudinal data or testing theories about affect dynamics. In this chapter, we give a brief overview of some of the computational models that have been applied in the field of affect dynamics, focusing on both discrete-time and continuous-time models. The emphasis of this chapter lies on describing the core ideas of the models and how they can be interpreted. At the end, we provide references to other important topics for the interested reader.

10.1 Introduction

Studying emotion dynamics, or how emotions change over time, implies that one has to collect intensive longitudinal data (ILD; i.e., longitudinal data with many measurements over time; Y. Chen & Zhang, 2020). Advances in technology have greatly facilitated the collection of such data (Hamaker et al., 2015), both in daily life (Bolger et al., 2003; Larson & Csikszentmihalyi, 1983; Myin-Germeys et al., 2018) and the laboratory (Seeley et al., 2015). When ILD have been collected, the challenge remains to analyze them and interpret the results. For this, we make use of *computational models*, that is, statistical or mathematical models that formalize how we believe a system works. In the case of emotion dynamics, these models formalize properties of ever-evolving emotions, so that they may change in their presence, intensity, and frequency over time.

However, formalizing the operation of the affective system is easier said than done. Luckily, the increased use of ILD has led to an increased interest in models

---

Niels Vanhasbroeck and Sigert Ariens contributed equally to this work.

N. Vanhasbroeck (✉) · S. Ariens · F. Tuerlinckx · T. Loossens
KU Leuven, Leuven, Belgium
e-mail: niels.vanhasbroeck@kuleuven.be

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_10

that quantify time-dependent changes in a whole range of psychological processes. Knowing what models exist and when it is appropriate to use them is thus tantamount for any researcher who wants to understand how emotions change over time.

In this chapter, some of the available computational models for temporal processes will be considered, with a focus on those models that have been used to study affect dynamics. The chapter will focus on computational models for the flow of emotional experiences, rather than models that zoom in on one specific emotional experience and how it unfolds over time (Kuppens & Verduyn, 2015; Verduyn et al., 2009).

10.1.1 Why Computational Models?

Why should we bother with these often complicated models of affect dynamics? To appreciate the role models may play in advancing research, we discern two general goals of their application and refer the interested reader to Breiman (2001) and Koopmans (2011) for a more elaborate discussion.

First, computational models can be used as data analysis tools. In this sense, they enable the researcher to study complex patterns of change in empirical data and validate hypotheses concerning these patterns (Hamaker et al., 2015). The way such computational models are being used is no different than ANOVA: It is a generic model that can be applied to a wide range of data without presuming that the model provides a complete account of the data generating process. The usefulness of such models is determined by whether they can account for some of the features observed in empirical data. For example, it is widely believed that the intensity of an emotional or mood state is in some way related to its past intensity (i.e., when one feels bad now, this will likely continue for some time; Kuppens & Verduyn, 2017). Models that do not take such relation into account, may be less appropriate for analyzing affective time series.

Secondly, computational models can be formulated as theories of affect dynamics (Farrell & Lewandowsky, 2010; Hamaker et al., 2015; Luce, 1995). Like verbal theories, they may describe how emotions behave over time and what underlies their fluctuations. Each model has its own focus or emphasis, as well as its own set of assumptions. Furthermore, it is possible to derive hypotheses and test them to provide either evidence for or against the model (Jekel, 2019).

There are some advantages to using these theoretical computational models compared to verbal theories (see Farrell & Lewandowsky, 2010 and Smaldino, 2017 for a more elaborate discussion). Firstly, defining a computational model forces us to specify all aspects of a theory in an explicit and detailed manner. Secondly, when multiple computational models describe the same process, comparison of model performance (i.e., how well a model describes empirical data) may guide us towards better theories of affect dynamics. Lastly, discussion about the theory does not rest upon the interpretation of others, but rather on the set of mathematical properties of the model. This limits misinterpretation of the theory and moves the literature away from communication of theories to the testing of them. However, here also lies a disadvantage of these models: They may be too technical to understand straightaway, which may still lead to misunderstanding of what these models can, and perhaps more importantly, cannot explain.

The boundary between a computational model that is used as an analysis tool and a computational model that is considered a theory is often fuzzy—the same model may be used as a data analysis tool by some and as a theoretical model by others. Therefore, we will use the term "computational model" in a general sense, referring to both instances.

10.1.2 Characteristics of Affective Time Series

As mentioned before, a minimal requirement for computational models of affect dynamics is that they take into account at least some features of emotional change. Here, we shortly discuss the most general characteristics of an affective time series that are accounted for by most computational models of affect, namely the *baseline*, *variability*, and *regulation* of the process.

Figure 10.1 provides an illustration of an affective time series in which the happiness of a single individual has been measured at 25 different time points. A first thing one may notice is that measured happiness fluctuates around the dotted line in the figure. This dotted line is called the baseline and represents the affective state that comes naturally to the individual, or the affective state in which the individual is most likely to find him-/herself. If happiness increases or decreases relative to this baseline, one would feel more or less happy than usual (Brickman & Campbell, 1971; Kuppens et al., 2010). The fact that happiness does not stick to the baseline, but shows some variability over time, is a second characteristic of the time series. This variability indicates that happiness is not a stable construct, but that it changes over time. Finally, when a grave change in happiness has occurred, it tends to move

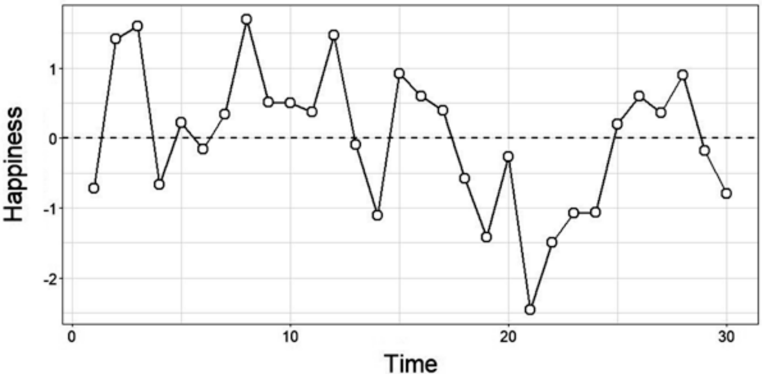


Fig. 10.1 Illustration of an affective time series

back towards the baseline (e.g., timepoint 21–25 in Fig. 10.1). In other words, affect is regulated back to the baseline: a third characteristic of affective time series (Gross, 2015; Kuppens & Verduyn, 2017).

In the subsequent parts of this chapter, we will introduce the reader to some computational models of affect dynamics. We make a distinction between *discrete-time* and *continuous-time* models—two classes of models that differ in how they treat time, which we will discuss later. In our discussion, we will not shy away from showing the mathematical equations of these models, as we deem it important to expose the interested reader to them before they might delve into the, often technical, literature around them. We follow some conventions for mathematical notation. Lowercase letters are used for scalars or single values. When they are in bold, however, they represent a collection of such scalars called *vectors*. Uppercase letters are used for matrices. Greek letters are used for parameters that should be estimated, while Roman letters describe observed values.

10.2 Discrete-Time Models

The class of *discrete-time* models enjoys a wide popularity in psychological research. These models relate measurements at a given time point to measurements at previous time points, usually by means of *difference equations* or *maps* (Strogatz, 2018). As such, discrete-time models describe changes in the affective time series in discrete steps, from one measurement to another.

First, we will introduce the *autoregressive models*, which are among the most prominent in the affect dynamics literature (Hamaker et al., 2015) and often serve as a building block for more complicated models. Afterwards, we will focus on *reinforcement learning models* as a more recently proposed class of models for affect dynamics.

10.2.1 Autoregressive Models

10.2.1.1 The Autoregressive Model

Imagine that we track someone's happiness across time, using a continuous slider ranging from 0 (*not happy*) to 100 (*extremely happy*). Let y_j (with $j \in \{0,1,\ldots,N\}$) denote the ratings obtained at time points $t_0 < \cdots < t_j < \cdots < t_N$. The lag-1 *autoregressive* or *AR(1)* model relates the rating $\mathrm{y_j}$ at time t_j to the rating y_{j-1} at time t_{j-1} (i.e., the immediate predecessor) by means of a linear regression:

$$y_j = \delta + \varphi y_{j-1} + \varepsilon_j$$

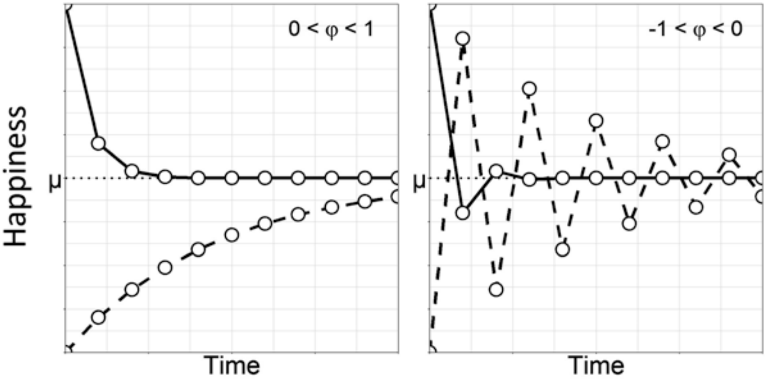


Fig. 10.2 Emotional fluctuations as captured by a standard AR model (without random noise). In the left plot, the autoregressive coefficient $\boldsymbol{\varphi}$ is positive, lying in the interval]0, 1[. This leads to an exponential decay, which becomes more gradual as $\boldsymbol{\varphi}$ approaches 1. In the right plot, $\boldsymbol{\varphi}$ is negative, lying in the interval]−1, 0[. This leads to emotional switching, in which the emotional state crosses the baseline at each future time point. The strength of this overshoot dies out over time, and is related to the size of $\boldsymbol{\varphi}$, so that values of $\boldsymbol{\varphi}$ closer to −1 lead to longer dying-out time. In the plots, the solid line is always generated by a small autoregressive effect ($\boldsymbol{\varphi} = -0.2$ or $\boldsymbol{\varphi} = 0.2$), while the dashed line is generated by a large autoregressive effect ($\boldsymbol{\varphi} = -0.8$ or $\boldsymbol{\varphi} = 0.8$)

The parameter δ is a constant referred to as the *intercept*. This intercept can take any value and is related (but not equal) to the baseline (see Appendix 1).

The parameter φ ($\in [-1,1]$) is called the *autoregressive coefficient*; it describes the temporal dependence of the variable y with itself at lag 1. In other words, it summarizes how strongly happiness scores depend on previous happiness scores. Values closer to −1 or 1 imply a strong temporal dependence, whereas values closer to zero imply that there is little to no carry-over effect. When this effect is positive, an initial happiness score is expected to be regulated towards the baseline exponentially fast. When it is negative, however, we expect happiness to overshoot the baseline with each additional measurement. This overshoot is damped, so that it dies out over time. These autoregressive effects are visualized in Fig. 10.2.

The stochastic variables ε_j are often referred to as the *innovations*. These are used to describe unpredictable effects due to internal and external processes, capturing the variability in the dependent variable. They are typically assumed to be uncorrelated over time, independent of past values of the variable y, and normally distributed with mean 0 and variance σ_{ε}^{2}:

$$\varepsilon_j \sim N\left(0,\sigma_{\varepsilon}^{2}\right)$$

Order The AR(1) model is a model of *order* 1 or lag 1. This means that the ratings y_j at times t_j are regressed on the ratings y_{j-1} at times t_{j-1}. However, the AR(1) model is generalizable to higher orders, so that emotional states further in the past may also contribute to an emotional state at present.

The AR(p) model of order p is defined as:

$$y_j = \delta + \sum_{p}^{k=1} \varphi_k y_{j-k} + \varepsilon_j,$$

where an autoregressive effect is assigned to each lagged variable y_{j-k}. In this chapter, we will confine ourselves to the discussion of models of order 1, although results may be generalized to models of order p. Because of this restriction, we will also simplify our notation from AR(1) to AR.

10.2.1.2 The Vector Autoregressive Model

In the context of affect dynamics researchers are usually interested in the change and interactions of multiple emotions or affective components over time. To accommodate this need, the AR model can be extended to take multiple variables into account—an extension also known as the vector autoregressive (VAR) model.

A VAR model with d variables is defined as:

$$\begin{gathered} \boldsymbol{y}_j = \delta + \Phi \boldsymbol{y}_{j-1} + \boldsymbol{\varepsilon}_j \\ \boldsymbol{\varepsilon}_j \sim N\left(\mathbf{0}, \Sigma_\varepsilon\right) \end{gathered} \tag{10.1}$$

with

$$\boldsymbol{y}_j = \begin{bmatrix} y_1 \\ \vdots \\ y_i \\ \vdots \\ y_d \\ \\ \end{bmatrix}_j, \delta = \begin{bmatrix} \delta_1 \\ \vdots \\ \delta_i \\ \vdots \\ \delta_d \\ \\ \end{bmatrix}, \boldsymbol{\varepsilon}_j = \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_i \\ \vdots \\ \varepsilon_d \\ \\ \end{bmatrix}_j$$

$$\Phi = \begin{bmatrix} \varphi_{11} & \cdots & \varphi_{1i'} & \cdots & \varphi_{1d} \\ \vdots & \ddots & \vdots & & \vdots \\ \varphi_{i1} & \cdots & \varphi_{ii'} & \cdots & \varphi_{id} \\ \vdots & & \vdots & \ddots & \vdots \\ \varphi_{d1} & \cdots & \varphi_{di'} & \cdots & \varphi_{dd} \end{bmatrix}, \Sigma_\varepsilon = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{1i'} & \cdots & \sigma_{1d} \\ \vdots & \ddots & \vdots & & \vdots \\ \sigma_{i1} & \cdots & \sigma_{ii'} & \cdots & \sigma_{id} \\ \vdots & & \vdots & \ddots & \vdots \\ \sigma_{d1} & \cdots & \sigma_{di'} & \cdots & \sigma_{dd} \end{bmatrix}$$

The values of the variables at time t_j are contained in the $d \times 1$ vector $\boldsymbol{y}_j$. The intercepts and innovations of each variable are contained in the $d \times 1$ vectors $\boldsymbol{\delta}$ and $\boldsymbol{\varepsilon}_j$. The autoregressive effects reside in the $d \times d$ transition *matrix* Φ—more specifically on its diagonal (i.e., φ_{ii} represents the autoregressive effect of variable y_i). The off-diagonal elements are called *crossregressive effects* and represent the temporal relations between the different variables. This means that a variable at time t_{j-1} may be related to another variable at time t_j. As an example, fatigue early in the day may be associated to irritability later in the day. Or being relaxed in the morning may be associated to feeling happier in the afternoon (if you did not miss any deadlines because you were a bit too relaxed, that is).

The (co)variances of the innovations are captured in the $d \times d$ innovation covariance matrix Σ_ε. The diagonal contains the variances of the variables and the off-diagonal elements coincide with the covariances between the variables. Allowing innovations to covary means that, on average, random perturbations to the first process at time t_j are not independent from perturbations to a different process at time t_j. Innovation covariance is therefore usually assumed to reflect common responses to external stimuli. Note that such innovation covariances are different from the direct lagged effects in that they do not make specific which of the two processes drives the other.

The VAR model has several interesting properties, such as regulation to a baseline, growing uncertainty of predictions further away in the future, and the possibility to derive the autocorrelation from the transition matrix (see Appendices A and B). Furthermore, it allows researchers to study complex patterns of affect dynamics without the requirement to make a priori decisions on parameter structure (see Fig. 10.3), so it can be applied to a wide range of problems. Because of its simplicity, its versatility, and its usefulness in describing basic properties of affect dynamics, it is no surprise that VAR models have received much attention in the field, both in the empirical (e.g., Congard et al., 2011; Kuppens et al., 2012a; Kuranova et al., 2020; Wichers et al., 2020) and statistical literature (e.g., Adolf et al., 2017; Bringmann et al., 2018; Bulteel et al., 2016). However, these advantages come at a price, as the large number of parameters requires a large amount of data to be estimated adequately (Loossens, Dejonckheere, Tuerlinckx, & Verdonck, 2021).

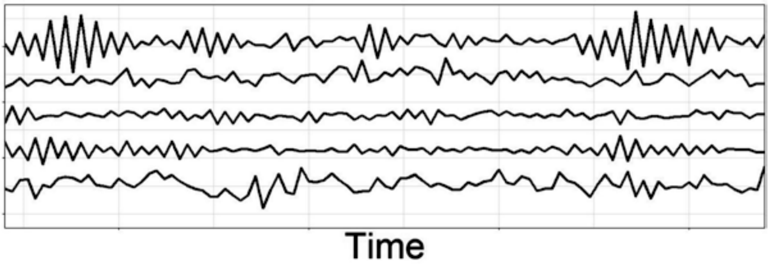


Fig. 10.3 Simulated trajectories for five variables of a VAR model. The VAR can capture many complicated, and often realistic patterns of emotional fluctuation that can be found in data

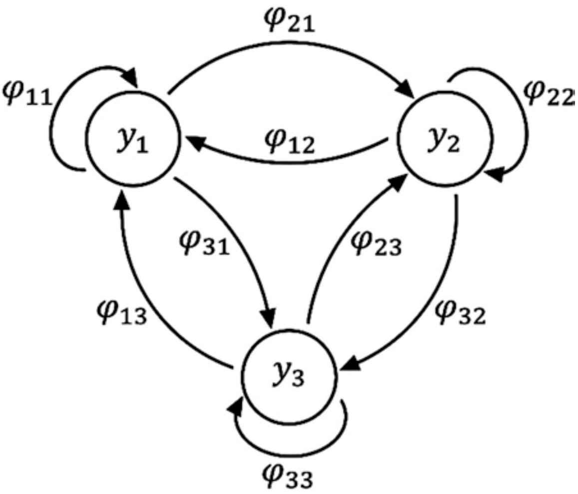


Fig. 10.4 Example of a directed network with three nodes and six unidirectional edges. The nodes of the network consist of three variables y_1, y_2, and y_3. The strength of the lagged associations between these variables is estimated by using the auto- and cross-regressive effects that reside in the transition matrix Φ of a VAR model

10.2.1.3 Network Models

A network model is a representation of how different observed variables are related to each other. In Fig. 10.4, an example of such as network is given, where different variables or *nodes* are associated to each other through their *edges*. These edges may be weighted and unweighted, such that in the former case, you estimate the strength of the association, while in the latter case you remain agnostic of the association strength. Edges can furthermore be directed or undirected, such that directed edges describe the unidirectional influence of node i on node i', while undirected edges describe the bidirectional influence between these two nodes (i.e., both nodes exert an equal influence on each other; Smith et al., 2018).

There are many ways to build network models, depending on the association measures used as the edges and the values of the variables. In affect dynamics, a VAR model is often used as a basis of network,[1] presenting results in a more approachable way, easing interpretation (Borsboom & Cramer, 2013; Bringmann et al., 2013; Bulteel et al., 2016; Epskamp, 2020a). Building a network model from an individual's affective time series can then be accomplished with a few basic steps. First, you define the nodes to be equal to the variables y. Then, you estimate the parameters of the VAR model and equate the (directed) edges to the auto- and crossregressive effect in the transition matrix Φ (see Fig. 10.4). Finally, the network is visualized and interpreted. These steps can be accomplished by using several R packages, such as *graphicalVAR* (Epskamp, 2020b; see also Epskamp et al., 2018) and *qgraph* (Epskamp et al., 2012). A network built on the transition matrix of a VAR model is temporal in nature, as the lagged association between the variables is

---

[1] Because of this, we present network models in the section on autoregressive models. This was a practical choice, and we do not mean to imply that network models are always autoregressive in nature. In fact, most networks are not (e.g., Ising models; Kruis & Maris, 2016).

used as an association measure. Such a network therefore shows how variables are expected to change over time.

The network approach has several advantages. First, it allows researchers to make graphs of the estimated network, which may aid interpretation of the results. Furthermore, network models allow the use of several measures that define characteristics of the network, such as *centrality* of nodes (i.e., how interconnected a specific node is) and *clustering* between different nodes (Borsboom & Cramer, 2013; Watts & Strogatz, 1998). Such measures have been used to define several characteristics of emotional networks. For example, it has been found that in patients, several symptoms cluster together and that these clusters are only connected to each other through *bridge symptoms* (e.g., Borsboom et al., 2011; Fried et al., 2017; Greene et al., 2020; but see Groen et al., 2020). Similarly, it has been found that positive and negative emotions cluster together (Bringmann et al., 2013).

Despite these advantages, there are also several interpretational issues with network models. First, network models are often conceptualized as complex systems consisting of causal agents (Epskamp, 2020a). In other words, the relation of one node to another is usually interpreted as a causal one, meaning that changes in one node cause changes in another node. However, research in affect dynamics is generally correlational in nature and therefore not amenable to causal analysis in the first place. As succinctly put by Box (1966), “To find out what happens to a system when you interfere with it you have to interfere with it (not just passively observe it)” (p. 629).

Another hazard is specific to networks built on VAR models. The use of a network approach may obscure some known sources of bias in the parameters of VAR models. Two sources of bias have been identified by Bulteel et al. (2016). Firstly, differences in the variability of the variables may lead to inflated or deflated association estimates. Secondly, auto- and crossregressive coefficients reflect unique direct effects, which means that when the variables are interrelated, a portion of the temporal relations between variables is ignored. This can be seen by calculating the autocorrelation $\rho_{t\ t-1}$ for variable y_1 in VAR model with two variables and with $\boldsymbol{\delta} = [0,0]'$, which is equal to (see Appendix 2):

$$\begin{aligned}\rho_{t,t-1} &= \frac{\varphi_{11}\sigma_1^2 + \varphi_{12}\sigma_{12}}{\sigma_1^2} \\ &= \varphi_{11} + \frac{\varphi_{12}\sigma_{12}}{\sigma_1^2}\end{aligned}$$

The autocorrelation calculated here represents the temporal relation of the variable to itself, and does not only depend on the autoregressive effect, but also on the crossregressive effect of y_2 on y_1, scaled (in part) by how much the two variables relate contemporaneously (captured by σ_{12}). Using only φ_{11} as a measure of autorelation in a network model may thus not capture the full relation, which can lead to erroneous conclusions. Only in a few situations can the autoregressive effect capture the full relation, namely when there is no covariance between the process variables (Bulteel et al., 2016).

10.2.1.4 Extensions

Many extensions to the AR and VAR models exist, and they are often introduced for one of two reasons. Firstly, they can be introduced to deal with some of the limitations of classical autoregressive models, such as the issue of *nonstationarity*. Secondly, extensions have been introduced to take the influence of contextual factors into account. Both reasons and their related extensions are discussed in detail below.

Nonstationarity. Stationary processes are processes that display *constant* statistical properties over time (Scargle, 1981). In other words, while emotions change over time, their means and (co)variances remain the same over time (see Appendix 1). For example, one's happiness will regulate back to the same baseline over and over again (e.g., Brickman & Campbell, 1971).

The AR-based models discussed in this section assume that the processes they model are stationary. However, that assumption may be overly restrictive. There may be situations in which we expect meaningful changes in the dynamical properties of a time series, for instance due to interventions, experimental manipulations, or major life events. Indeed, nonstationary time series have been observed in affect dynamics in clinical populations (Bonsall et al., 2012; Nelson et al., 2017; van de Leemput et al., 2014) and in situations where the environment has a meaningful (and possibly enduring) influence on an individuals' affect dynamics (Dunn et al., 2018). Studying nonstationarity and its origins may therefore be relevant, since it could, for instance, signal an individual's transition from a healthy state to mood disorders (van de Leemput et al., 2014).

Nonstationarity is a broad concept: Changes in mean, covariance, and higher order statistical moments can occur suddenly or gradually, or even display recurring patterns over time (e.g., Chow et al., 2005; Larsen et al., 2009). Sometimes researchers may have explicit hypotheses about likely sources of nonstationarity. Other times researchers may instead wish to treat nonstationarity as a nuisance that should be taken care of prior to the actual analysis. Each of these distinctions has implications for how one should deal with nonstationarity (see also Hamaker & Wichers, 2017). The topic is thus vast, and many approaches to modeling nonstationary series have been suggested. Here, we will only consider model-based solutions. For data-driven ways of handling nonstationarity prior to analysis (such as differencing and detrending), we refer the reader to Box and Jenkins (1970), Dickey and Fuller (1979), Hamilton (1994b), Lütkepohl and Xu (2012), and Velicer and Molenaar (2012).

Time-Varying VAR An intuitive extension of the typical VAR model is to allow some of its parameters to change over time, which is exactly what the time-varying

VAR (tvVAR) does (Bringmann et al., 2018). The general model for order 1 would be:

$$\boldsymbol{y}_j = \boldsymbol{\delta}_j + \Phi_j \boldsymbol{y}_{j-1} + \boldsymbol{\varepsilon}_j$$
$$\boldsymbol{\varepsilon}_j \sim N\left(\mathbf{0}, \Sigma_\varepsilon\right)$$

with

$$\boldsymbol{\delta}_j = \boldsymbol{f}\left(t_j\right)$$
$$\Phi_j = g\left(t_j\right)$$

where the index j in $\boldsymbol{\delta}_j$ and Φ_j indicates that these components change over time. The functions $\boldsymbol{f}(t_j)$ and $g(t_j)$ are smooth functions of time and are estimated using regression splines (for more details and an empirical application, see Bringmann et al., 2018).

Despite its intuitive appeal and applicability for exploratory analyses, this model typically needs a lot of data in order to be estimated accurately. Furthermore, the multivariate version of this model fixes the innovation covariances to zero, indicating that it cannot—at present—capture contemporaneous relations between variables.

Regime-Switching Models An alternative method is applicable to situations in which dynamical features change abruptly. One type of models that incorporates these abrupt changes are the regime-switching models (Cabrieto et al., 2018; Hamilton, 2010). These regimes consist of separately estimated VAR models, thus allowing regimes to be different on all kinds of dynamical features. The way in which one switches regimes depends on assumptions made by the researcher. For example, Markov regime-switching models determine these shifts by a hidden Markov model (Hamilton, 2010). Another possibility is to formalize an hypothesized relationship between the probability of switching and an observed covariate. These models are typically called threshold autoregressive models (Tong, 2011).

In general, regime-switching models can be formalized as:

$$\boldsymbol{y}_j = \boldsymbol{\delta}_{r_j} + \Phi_{r_j} \boldsymbol{y}_{j-1} + \Psi_{r_j} \boldsymbol{\varepsilon}_j$$
$$\boldsymbol{\varepsilon}_j \sim N\left(\mathbf{0}, \Sigma_\varepsilon\right)$$

where the model coefficients depend on the value of r_j, denoting the regime r at time t_j. The matrix Ψ allows for regime-dependent innovations without explicitly changing the innovation matrix in a specific regime. To determine switching, a latent estimate of the probability p_{kl} of switching from regime k to regime l is made:

$$p_{kl} = P\left(r_j = l \mid r_{j-1} = k\right)$$

While these models have been successfully used in the context of affect dynamics (e.g., switching between depressive and manic states in bipolar disorder; Bonsall et al., 2012; transitioning from healthy to depressive state; Albers & Bringmann, 2020), they suffer from the limitation that they require more than one model to capture the complete time series (Hamilton, 2010). As a consequence, the number of parameters to be estimated substantially increases with each additional regime. To be able to estimate such a model reliably, sufficiently long time series are required.

Context. Until now, the models have assumed that the emotional system evolves in a contextual vacuum. We have often referred to the dependent variables as reflecting affect, without including any external contextual information in the model. Nonetheless, the inclusion of contextual information in computational models may greatly enhance our understanding of how events may elicit emotions, which aspects of the emotional process are influenced, what the emotional system does when it anticipates them, and how long these emotions last (Daros et al., 2019; Voelkle et al., 2013).

Fixed Moderated VAR One way in which such information can be included is fixed moderated VAR (fmVAR, Adolf et al., 2017), an extension of the VAR framework which allows parameters to change depending on the value of a lagged external variable, by including it as a moderator variable. The general model can be formulated as:

$$\boldsymbol{y}_j = \boldsymbol{\delta}_j^* + \Phi_j^* \boldsymbol{y}_{j-1} + \boldsymbol{\varepsilon}_j$$
$$\boldsymbol{\varepsilon}_j \sim N\left(\mathbf{0}, \Sigma_{\varepsilon j}^*\right)$$

with

$$\boldsymbol{\delta}_j^* = \boldsymbol{f}\left(\boldsymbol{x}_{j-1}\right)$$
$$\Phi_j^* = g\left(\boldsymbol{x}_{j-1}\right)$$
$$\Sigma_j^* = h\left(\boldsymbol{x}_{j-1}\right)$$

where $\boldsymbol{x}$ is a vector of values of the moderator at each time point.

The functions $\boldsymbol{f}$, g, and h are *link functions* which define the functional form of how the moderator influences the process. For example, a linear link function for δ_j^* would assume a linear relationship between the moderator and the intercept of the process $\boldsymbol{\delta}$. This is a relatively straightforward way of accommodating changes in the level of the series, for instance by tying a dummy-coded moderator signaling a major life event to the process intercept.

Note that the moderator is assumed to be observed and measured without error. As such, fmVAR models are in particular applicable to situations in which contextual factors are controlled by the researcher like, most notably, in lab studies. Missing moderator values cannot be handled within the model, which need to be imputed a priori (Adolf et al., 2017).

10.2.2 *Reinforcement Learning*

Where autoregressive models (and most other models in this chapter) mainly describe relations between variables, *reinforcement learning models* go a step further and link environment with emotions in a more explicit way.[2] Reinforcement learning is a computational framework that describes how an agent or individual uses its experience to update its behavior, often with the goal of maximizing future rewards (Bennett et al., 2020; Sutton & Barto, 2018). Central to this framework is the notion that we get feedback on our actions, which is then used to change our behavior. To make this more concrete: imagine a child that gets caught taking candy from the cupboard without asking first. The parents may be very angry with the child, an outcome he/she probably does not like. In light of this feedback, the child may then change his/her future behavior and ask the parents for candy first (or perhaps steal the candy more stealthily). Reinforcement learning thus provides a way to integrate emotional states with environmental cues, goals, and behavior, bringing action tendencies to computational modeling (Frijda, 2007).

We discuss two reinforcement learning-based models, one that is only concerned with explaining emotional states (Rutledge et al., 2014; Villano et al., 2020) and another that links these emotional states to behavior and learning biases (Bennett et al., 2020). These are, however, not the only models in this rich field (see e.g., Doll et al., 2012; Eldar & Niv, 2015; Eldar et al., 2015; Sutton & Barto, 2018).

10.2.2.1 Computational Model of Happiness

This unnamed model was originally proposed by Rutledge et al. (2014) and has been used by several other authors (e.g., Villano et al., 2020; Vinckier et al., 2018). It was proposed within the context of a study on the influence of gambling outcomes on fluctuations in happiness. For this, Rutledge et al. (2014) used a gambling experiment in which participants had to choose between a certain reward (value c) or a gamble. When participants choose a gamble, they had a 50/50 probability of receiving a higher (denoted as h) or lower outcome (denoted as l) than the certain reward. The reward given at the end of the trial can be denoted as o. Based on this experiment, the model was formulated as[3]:

---

[2] Note that we specifically talk about reinforcement learning in the context of emotion dynamics: This class of model is applicable to many more subjects, like decision-making, conditioning, and learned behavior (see Sutton & Barto, 2018).

[3] To remain in line with the mathematical notations of this chapter, we changed the notation of this model (see Rutledge et al., 2014).

$$y_j = \delta + \omega_1 \sum_{j}^{i=1} \gamma^{j-i} c_i + \omega_2 \sum_{j}^{i=1} \gamma^{j-i} v_i + \omega_3 \sum_{j}^{i=1} \gamma^{j-i} p_i + \varepsilon_j$$

$$\varepsilon_j \sim N\left(0, \sigma^2\right)$$

where δ is the intercept, and the variables c, v $(= \frac{(h+l)}{2})$, and p $(= o - v)$ represent the value of the certain reward, the expected value of the gamble, and the reward prediction error (i.e., the difference between the obtained reward and the expected value). Note that for trials in which the gamble is chosen, c is zero, and for trials in which the certain reward is chosen, v and p are zero. Importantly, past outcomes also play a role, although their influence decays over time. This decay is captured by the value of γ $(\in [0,1[)$, which is called the forgetting factor (see Rutledge et al., 2014). The greater the value of γ, the longer the rewards linger and the greater their influence on current happiness. The influence of all rewards (both at the current time point as well as the previous ones) is scaled by the ω's. With this model, Rutledge et al. (2014) found that prediction errors are an important driver of fluctuations in happiness, a result that has subsequently been confirmed by Rutledge et al. (2017) and Vanhasbroeck et al. (2021).

A limitation of the model is that it can only be applied to situations in which there is a certain and uncertain outcome. However, in reality, rewards may always be uncertain. To accommodate this limitation, Villano et al. (2020) made a small adjustment to the model:

$$y_j = \delta + \omega_1 \sum_{j}^{i=1} \gamma^{j-i} o_i + \omega_2 \sum_{j}^{i=1} \gamma^{j-i} p_i + \varepsilon_j$$

$$\varepsilon_j \sim N\left(0, \sigma^2\right)$$

where p represents the prediction error and o the uncertain outcome. With this adjusted model, Villano et al. (2020) also found that prediction error is an important driver of fluctuations in affect in daily life.

10.2.2.2 Integrated Advantage Model of Mood

While the previous models were able to establish the role of prediction error in affect dynamics, they do not specify how happiness or affect may guide behaviors. The Integrated Advantage Model of Mood (IAMM) goes a step further and explicitly links behavior to mood, and mood biases to behavior (see Bennett et al., 2020). In this chapter, we limit our discussion to the basics of the IAMM, leaving out some of the details of the model. We refer the interested reader to the preprint of Bennett et al. (2020) for a more thorough discussion of the model.

Central to the IAMM is the notion of *advantage*, which can be defined as the difference between the outcome of a chosen action and the value of the state within which this action has been taken (Bennett et al., 2020). More concretely, advantage tells you something about how well you are doing now compared to before. Let's return to the example of the child: the child craved some candy (a low-valued state), so he/she decided to look in the cupboard and take some candy (an action), after which the craving is satiated (a high-valued state). The advantage of the child's action is thus positive, as he/she moves from a low- to a high-valued state. This advantage may lead to a strengthening of this behavior, i.e., the child may choose to act this way again in the future. If, however, at some point the parents catch him/her, the child suddenly find him/herself in a low-valued state again, decreasing the advantage of this same action. As such, the overall advantage of the action "taking candy" may depend on how many times the child was able to take candy without being caught, and on how the child values angering the parents (e.g., if a child does not really care that the parents are angry, then he/she will probably continue acting the same way).

Based on this notion of advantage, the IAMM defines mood that results from an action as:

$$y_j = y_{j-1} + \eta\left(\hat{\alpha}^{\pi}\left(s_{j-1}, a_{j-1}\right) - y_{j-1}\right) \tag{10.2}$$

where η plays a similar role as the parameter γ in the model of Rutledge et al. (2014), and where $\hat{\alpha}^{\pi}\left(s,a\right)$ is the estimated advantage of doing action a (taking candy) in situation s (craving candy) under a certain behavioral policy π. The behavioral policy can be seen as a rulebook that links actions to situations. For example, in the situation "craving candy", the action "taking candy" may be more likely taken than the action "asking parents first". However, based on the new experience of the child, and the associated negative advantage of performing this action, its probability may decrease. As such, $\hat{\alpha}^{\pi}\left(s,a\right)$ plays a crucial role in updating the policy π. The IAMM thus goes further than just describing mood states: It also describes how advantage can change behavioral tendencies over time (Bennett et al., 2020).

This is, however, only part of the story. Bennett et al. (2020) suggest that behavioral updating—based on advantage of an action—may be influenced by mood in the form of *momentum*. Momentum is a term from machine learning that describes an optimization algorithm for estimating parameters in which information of past updates is integrated with information on newly proposed ones (Rojas, 1996).

In terms of behavior, this comes down to the following: Suppose we act in a way that leads to positive advantage, then this advantage will lead to elevated mood and behavioral updating. Because of our elevated mood, we will also be more likely to update our behavior in the future (in combination with advantage, that is). In mathematical terms, this comes down to the updating of the parameters θ of the behavioral policy π, the details of which can be found in the preprint of Bennett et al. (2020).

$$\varepsilon_j = \lambda \varepsilon_{j-1} + \nabla_\theta \log\left(\pi\left(a_j \mid s_j\right)\right)$$

$$u_j = \zeta \varepsilon_j \left(\widehat{\alpha}^\pi \left(s_j, a_j\right) + \frac{1-\eta}{\eta} y_j \right)$$

$$\theta \leftarrow \theta + u_j$$

where υ represents the update in the parameters $\boldsymbol{\theta}$ of the behavioral policy, thus updating behavioral tendencies. Without going into detail, we will note that ε is the *eligibility trace* of the model, which determines the sensitivity with which certain action tendencies will update, depending on whether they were important in generating the taken action.

The question remains how one estimates the advantage of an action. Bennett et al. (2020) propose several estimators that may be used, one of which is the prediction error. A full description of these estimators is, however, beyond the scope of this chapter. If one is interested in knowing more about the model, we encourage the reader to read the preprint of Bennett et al. (2020).

10.2.2.3 Limitations

Reinforcement learning models have the clear advantage that they combine individual and environment in a more explicit way than is typically done by using autoregressive models. They can take into account the learning history of an individual (e.g., learned regulation strategies; Gross, 2015; learned action tendencies; Frijda, 2007) and biased reward perception (Mason et al., 2017). As such, it is no surprise that reinforcement learning-based models have been suggested as theoretical models of mood disorders (Bennett & Niv, 2018, June 7; Eldar et al., 2015).

A disadvantage of these models, however, is their reliance on known rewards: In order for the models to be estimated accurately, you should have reliable information about rewards received after performing given actions and the value that is attached to them by the individual. This information may not always be available (e.g., rewards may be intrinsic), which may influence the estimation of the parameters of the models. This makes reinforcement learning models ideal to analyze experimental data, but more difficult to apply to data from more naturalistic studies (e.g., daily life studies).

10.3 Continuous-Time Models

Why do we refer to discrete-time models as *discrete-time* models? A discrete-time model relates (or maps) observations at the discrete time points t_{j-1} to observations at the discrete time points t_j. In other words, discrete-time models are only concerned with how the process changes from one measurement to the next. With such mapping comes the assumption that all observations are separated by precisely the same time interval. A failure to meet this assumption has been found to bias parameter estimates (de Haan-Rietdijk et al., 2017; Hamaker & Wichers, 2017). The problem is that this requirement is nigh impossible to achieve in practice, so we may assume that most (if not all) applications of these models will lead to biased estimates. While some methods have been proposed to limit this bias, no perfect solutions exist within the discrete-time approach (de Haan-Rietdijk et al., 2017; Rindskopf, 1984).

Continuous-time models constitute another solution to this problem. These models attempt to estimate the function of the continuously-evolving variables with the use of *differential equations*, which have the advantage of incorporating change at any time interval by explicitly accounting for time (Deboeck, 2013; Strogatz, 2018). This mindset makes for an arguably more natural way of thinking about affective processes, which do not stop and wait for a next observation to express themselves, but evolve continuously over time (Cunningham et al., 2013; Ekman, 1992; Feldman Barrett, 2009; Frijda, 2007; Moors & Fischer, 2019; Scherer, 2005). Because of this continuity-assumption, emotions may inherently be better off being studied in continuous time (Boker, 2002). Furthermore, continuous-time models can deal with unequal time intervals between measurements, which may be better for ecological validity (Hektner et al., 2006) and for capturing relevant information about the underlying process (Voelkle & Oud, 2013).

10.3.1 Differential Equations

Continuous-time models are often differential equations, which relate the current value of a variable to the speed with which this same variable is regulated towards its baseline. In the context of affect dynamics, this implies that the strength with which a certain affective state is regulated, depends on the severity of the disruption of affect.

Because we provide mathematical formula for the models in this section, it is important to have a notion of what differential equations look like and how they can be interpreted. Our introduction is not exhaustive. We refer the interested reader to Deboeck (2013) for a low-level treatment of differential equations, and to Strogatz (2018) for a more thorough introduction to differential equations.

Differential equations can be written in a few, analogous ways, namely:

$$\frac{dy(t)}{dt} = f(y(t))$$
$$dy(t) = f(y(t))dt$$
$$\dot{y}(t) = f(y(t))$$

where *f* is a function of the variable, which may be linear or nonlinear (see later), and deterministic or stochastic (i.e., with or without a random component). In these equations, we can think of $dy(t)$ as being a change in value of the variable $y(t)$, and dt as a change in time. Hence, in the first notation, the left side represents the speed with which the variable $y(t)$ changes (change in the variable divided by a change in time), which is then related to the current value of the variable on the right side. In the second notation, the change in time dt is moved to the right side of the equation, so that you now relate the change in the variable $y(t)$ directly to the current state of the variable and the amount of time that has passed. The third notation is equivalent to the first one, so that $\dot{y}(t) = {}^{dy(t)}\!/_{dt}$. Personally, we prefer the second notation, and will try to use it where possible. In case the differential equations would become too complicated, however, we will use the first, standard notation.

10.3.1.1 Interpretation

The interpretation of differential equations may seem more alien than that of discrete-time models. However, there are several methods that make interpretation of continuous-time models easier. Besides directly interpreting the parameters (when they have clear-cut meanings), we will focus on one other method, namely considering the *vector fields*. For additional methods, we refer the reader to Ryan et al. (2018) and Strogatz (2018).

Plotting the vector field of a differential equation probably constitutes the most straightforward way for their interpretation (Strogatz, 2018). Vector fields represent the expected trajectories of emotional change, given specific initial conditions.[4] Plotting them thus provides us with some interesting characteristics of emotional change, such as the location of the baseline, the expected evolution of emotions, and the strength of regulation. Consider Fig. 10.5 in which different one- (top) and two-dimensional (bottom) vector fields are plotted. In panels (A) and (B), the derivative $\dot{y}(t)$ is plotted against the value of $y(t)$. In panel (A), it can be seen that when $y(t)$ is greater than 0, the derivative is lower than 0 (and vice-versa when $y(t)$ is lower than 0). This means that if $y(t)$ is greater than 0, it will move towards lower values of $y(t)$ with a speed that is determined by $\dot{y}(t)$. This movement stops when $\dot{y}(t)$ is equal to 0. The value of $y(t)$ in which this occurs is called a *fixed point*, and in this case the attractor, as values of $y(t)$ are regulated towards it (see the arrows). In panel (B), we see an opposite pattern, such $y(t)$ moves away from the fixed point, making it a *repellor* (note that if $y(t) = 0$, it stays put and does not move away from this fixed point). In panels (C) and (D), two equivalent vector fields for two-dimensional systems are shown with either arrows (size of the arrow indicates velocity of regulation) or trajectories.

---

[4] Importantly, this implies that vector fields are deterministic—they show what the model would expect if there were no perturbations to the system.

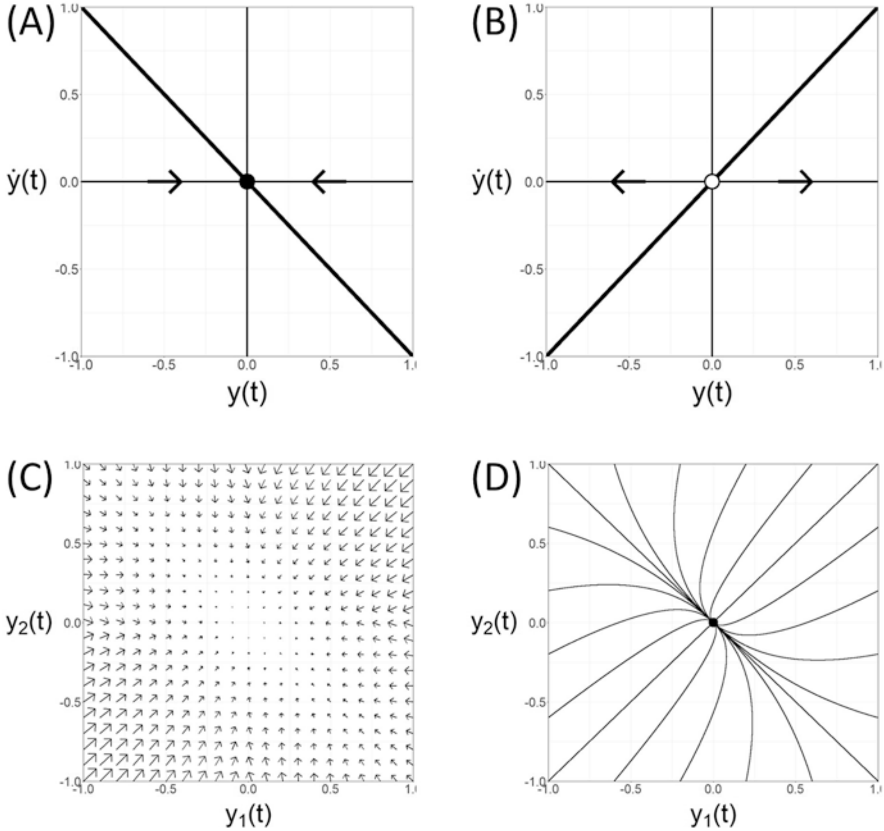


Fig. 10.5 Examples of vector fields for one- and two-dimensional systems. In plot (**A**), the derivative $\dot{y}(t)$ is plotted against the variable $y(t)$, resulting in a one-dimensional vector field. This vector field is specific to the simple system $\dot{y}(t) = -y(t)$, in which speed of regulation is linearly related to the emotional state. Arrows indicate the value to which the emotional state is regulated (here, the origin). This value is known as an *attractor*. In plot (**B**), another one-dimensional vector field is shown, this time for the system $\dot{y}(t) = y(t)$. Now, there is no regulation, but rather explosion of the emotional system, as indicated by the arrows. The origin takes on the role of *repellor*, which repels, rather than attracts values of $y(t)$. Plots (**C**) and (**D**) show two-dimensional vector fields with an attractor. In plot (**C**), direction and strength of regulation is shown through the use of arrows that differ in size. In plot (**D**), the deterministic trajectories towards the attractor are shown as solid lines

Constructing one- to two-dimensional vector fields can be achieved by following the following steps: (a) specify the parameters of the model to plot, (b) specify the initial condition of $y(t)$, (c) compute a trajectory from this initial condition for a specific amount of time, and (d) compute other trajectories and plotting them together. To approximate a trajectory, one can make use of the Euler method (Strogatz, 2018):

$$\begin{aligned}\Delta y_t &= y_t \Delta_t \\ y_{t+1} &= y_t - \Delta y_t\end{aligned}$$

where Δy_t represents the discretized change in the variable $y(t)$, and Δt represents the discretized change in time. In practice, you should choose Δt to be small enough so that the system does not fully return to baseline from the first go, but also not too small so that you can barely see any regulation. Other approximation methods exist as well, but will not be reviewed here (see Strogatz, 2018). Some software allows you to create such vector fields through the use of a function (e.g., *dynr*; Ou et al., 2019).

We will begin our discussion with linear continuous-time models of affect dynamics. These models are of the form (Strogatz, 2018):

$$d\boldsymbol{y}(t) = A\boldsymbol{y}(t)dt + c \tag{10.3}$$

where c denotes a collection of terms that does not depend on the state vector $\boldsymbol{y}(t)$ and A is a $d \times d$ matrix.

10.3.2 Linear models

10.3.2.1 Continuous-Time VAR

In the psychological literature, the term *continuous-time VAR* model is sometimes used as a synonym for the *Ornstein-Uhlenbeck* (OU) model, named after Ornstein and Uhlenbeck who formalized the properties of this continuous-time model (Uhlenbeck & Ornstein, 1930). This is because the OU model and the discrete-time VAR(1) model are closely related: if y(t) is a continuous-time OU process (e.g., happiness) and you take equally-spaced measurements of it, then the resulting observations behave according to a discrete-time VAR(1) model (for more details on the relation between the OU and discrete-time VAR(1), we refer the interested reader to Bergstrom, 1984; Oud, 2007; Oud & Jansen, 2000; see also Fig. 10.6). Because of this simple relationship, the OU model has been proposed as an alternative analysis tool for emotion data (Driver & Voelkle, 2018a; Voelkle & Oud, 2013), and is slowly being used by researchers (e.g., Booij et al., 2020; Guthier et al., 2020; Kuppens et al., 2010; Steele et al., 2018). For brevity, we will use the term OU model to denote the continuous-time VAR model and we will keep on using the term VAR model to denote the discrete-time VAR model.

The OU model is defined as (following Oravecz et al., 2011; related formulations by Deboeck & Preacher, 2016; Driver & Voelkle, 2018b; Oud & Jansen, 2000; Voelkle & Oud, 2013):

$$d\boldsymbol{y}(t) = \Theta\big(\mu - \boldsymbol{y}(t)\big)dt + \Gamma d\boldsymbol{w}(t) \tag{10.4}$$

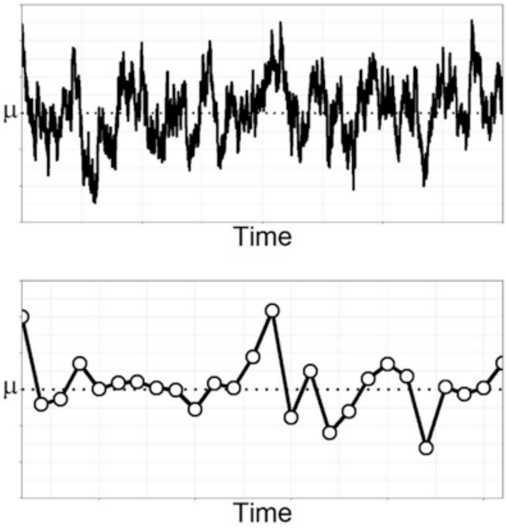


Fig. 10.6 Simulated data of an OU model (top) and associated equidistant measurements (bottom). These measurements can be described by a VAR model

with

$$\boldsymbol{y}(t)=\begin{bmatrix} y_1(t) \\ \vdots \\ y_i(t) \\ \vdots \\ y_d(t) \end{bmatrix}, \boldsymbol{\mu}=\begin{bmatrix} \mu_1 \\ \vdots \\ \mu_i \\ \vdots \\ \mu_d \end{bmatrix}, \boldsymbol{w}(t)=\begin{bmatrix} w_1(t) \\ \vdots \\ w_i(t) \\ \vdots \\ w_d(t) \end{bmatrix}$$

$$\Theta=\begin{bmatrix} \theta_{11} & \cdots & \theta_{1i'} & \cdots & \theta_{1d} \\ \vdots & \ddots & \vdots & & \vdots \\ \theta_{i1} & \cdots & \theta_{ii'} & \cdots & \theta_{id} \\ \vdots & & \vdots & \ddots & \vdots \\ \theta_{d1} & \cdots & \theta_{di'} & \cdots & \theta_{dd} \end{bmatrix}, \Gamma=\begin{bmatrix} \gamma_{11} & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & & \vdots \\ \gamma_{i1} & \cdots & \gamma_{ii'} & \cdots & 0 \\ \vdots & & \vdots & \ddots & \vdots \\ \gamma_{d1} & \cdots & \gamma_{di'} & \cdots & \gamma_{dd} \end{bmatrix}$$

The vector $\boldsymbol{\mu}$ is a constant vector that represents the baseline or attractor. Regulation of $\boldsymbol{y}(t)$ towards $\boldsymbol{\mu}$ is determined by the $d \times d$ matrix Θ, also known as the *drift matrix*. It fulfills a similar role as the matrix Φ for the VAR model (see Eq. (10.1)), but they are not the same: Θ is a nonlinear transformation of Φ that describes regulation on an infinitesimal time scale (see e.g., Oud, 2007).

Equation (10.4) is a *stochastic differential equation*. It does not only include a deterministic part (also known as *drift term*), but also a stochastic part (also known as *diffusion term*). This stochasticity comes about through the time-dependent fluctuations generated by d independent Wiener processes contained within the vector $\boldsymbol{w}(t)$. These fluctuations are scaled by the $d \times d$ lower-triangular matrix Γ. This matrix is not the continuous-time extension of the innovation matrix of the VAR model, but the latter can be computed from the former as $\Sigma = \Gamma\Gamma^T$.

The OU model, like the VAR model, is very general, which means that it can be a good exploratory tool, but in itself it says little about what the emotional system looks like. Nevertheless, we know of two theoretical applications of the OU model, one of which we turn to next.[5]

DynAffect. DynAffect is a theoretical OU model that assumes that fluctuations in affect occur within a two-dimensional valence-arousal affective structure (Kuppens et al., 2010; Oravecz et al., 2011). As a theoretical model for affect dynamics, it assumes that (a) there is a baseline to which individuals regulate their emotions, (b) the strength of regulation depends on the distance from the current affective state to this baseline, and (c) there are individual differences to be found in the baseline and regulation strength.

Evidence from a number of studies supports each of these assumptions (Kuppens et al., 2010; Oravecz et al., 2018; Oravecz & Brick, 2019; Wood et al., 2018). But, these assumptions are also very general. As such, their a priori probability of being true may be great, and the lack of falsification is thus less informative than one may have initially anticipated (Popper, 1959). Even so, DynAffect is a useful model of affect dynamics, as it provides a structural framework that can be used by other researchers (e.g., Pellert et al., 2020; Schweitzer & Garcia, 2010) and allows the investigation of individual differences in affect dynamics (e.g., Santangelo et al., 2016; Wood et al., 2018).

10.3.2.2 Damped Linear Oscillator

The *damped linear oscillator* is a linear model that has been specifically proposed to capture regulatory processes (Boker & Nesselroade, 2002; Chow et al., 2005; Hu et al., 2014; Steele & Ferrer, 2011). In physics, the damped linear oscillator is a well-known model for a pendulum that slows down due to friction (and of the movements of a spring in a viscous fluid, but we believe the pendulum speaks more to the imagination). When we instigate the movement of a pendulum, we can see its mass swing down to a central position, and then back up to the other side, only to swing down on a following turn. Each oscillation, i.e. each time the pendulum swings back, the amplitude of the swing will decrease, until at some point, the mass reaches a resting state (Boker & Graham, 1998). Another analogy is that of a thermostat: If we increase the temperature of the room, the room will heat up and slightly overshoot the specified temperature. It will then cool down until it overshoots the same temperature, after which it will heat up again (and vice-versa for decreasing the temperature of the room; Boker & Nesselroade, 2002; Chow et al., 2005). These movements are visualized in Fig. 10.7.

---

[5] In the application that we do not discuss, the OU model was only part of a series of equations (see Pellert et al., 2020; Schweitzer & Garcia, 2010).

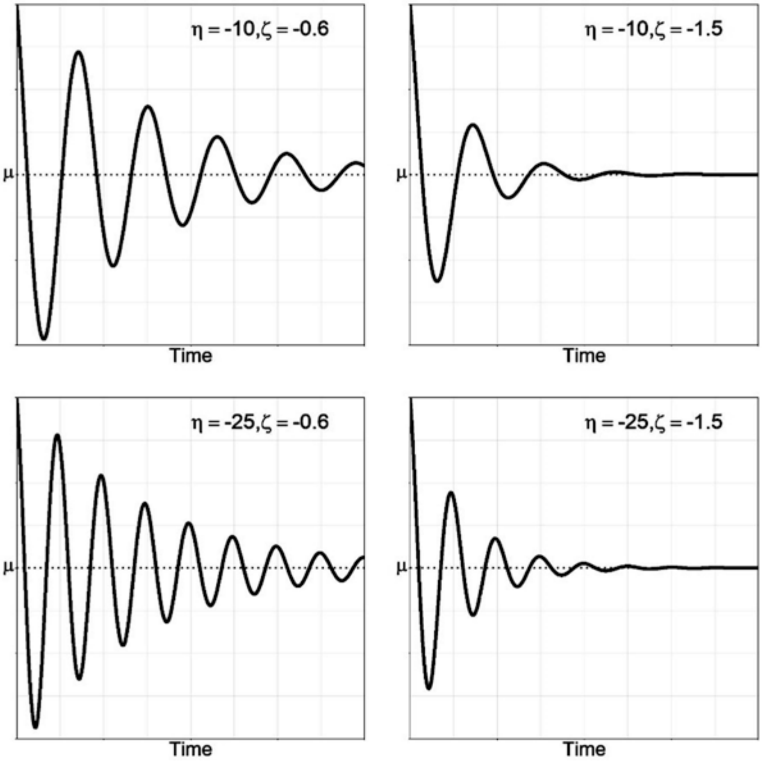


Fig. 10.7 Examples of regulation patterns to be expected by the damped linear oscillator (for one-dimensional systems). The trajectories were generated for a same initial condition and a same amount of time. When we decrease the value of η, we create a greater frequency of oscillations, visible in the number of times $y(t)$ overshoots the baseline (compare this for values $\eta = -10$ and $\eta = -25$). When we decrease the value of ζ, we increase damping, meaning that the overshoot will die out sooner (compare this for values $\zeta = -0.6$ and $\zeta = -1.5$). Note that these expected trajectories resemble the ones for negative autoregressive effects in the AR model (see Fig. 10.2)

Based on these examples, one may start to see why this model has been proposed as a model of regulation: When an event happens, we tend to regulate our ensuing emotions to return to our baseline (although upregulation may also occur; Gross, 2015). However, we may initially overregulate our emotions, such that we overshoot the baseline. After some time, this overshoot dies out and we eventually reach our resting state.

The (multivariate) damped linear oscillator is defined as follows[6]:

---

[6] The damped linear oscillator is an example of a *second-order differential equation*, where speed and location of a variable y at time t are both related to changes in speed over time (i.e., acceleration; speeding up or slowing down over time).

$$\frac{d^2\boldsymbol{y}(t)}{dt^2} = E\boldsymbol{y}(t) + Z\frac{d\boldsymbol{y}(t)}{dt}$$

with,

$$\mathrm{E} = \begin{bmatrix} \eta_{11} & \cdots & \eta_{1i'} & \cdots & \eta_{1d} \\ \vdots & \ddots & \vdots & & \vdots \\ \eta_{i1} & \cdots & \eta_{ii'} & \cdots & \eta_{id} \\ \vdots & & \vdots & \ddots & \vdots \\ \eta_{d1} & \cdots & \eta_{di'} & \cdots & \eta_{dd} \end{bmatrix}, \mathrm{Z} = \begin{bmatrix} \zeta_{11} & \cdots & \zeta_{1i'} & \cdots & \zeta_{1d} \\ \vdots & \ddots & \vdots & & \vdots \\ \zeta_{i1} & \cdots & \zeta_{ii'} & \cdots & \zeta_{id} \\ \vdots & & \vdots & \ddots & \vdots \\ \zeta_{d1} & \cdots & \zeta_{di'} & \cdots & \zeta_{dd} \end{bmatrix}$$

In these equations, the matrix E determines the frequency of the oscillations, i.e. how fast one regulates their emotions. Importantly, its diagonal elements capture the self-regulation of the variables (i.e., how fast the variables $\boldsymbol{y}(t)$ are regulated on their own), while the off-diagonal elements capture co-regulation of variables (i.e., how does the regulation of one variable relate to regulation of another). The matrix Z determines the amount of damping on the process, thus controlling how much one overshoots the baseline. In Fig. 10.7, one can see the impact of E and Z on the expected process for a one-dimensional system.

This model has been applied in a number of studies, often in the context of emotion dynamics in couples (e.g., Boker & Laurenceau, 2006; Reed et al., 2015; Steele & Ferrer, 2011), but also in the context of the relation between affective states and psychopathological symptoms (e.g., Hu et al., 2014). It can account for some interesting patterns in the data (although these are not unique, see Strogatz, 2018; Voelkle & Oud, 2013) and allows the estimation of theoretically meaningful parameters. Nevertheless, the model also has its downside. In its current form, it assumes that emotions die out over time. While this is no problematic assumption when examining specific emotional experiences, it may be more difficult to maintain when examining affect dynamics in real life, where a succession of affect-eliciting events may obscure such an (idealized) pattern. In practice, this issue is accounted for by including a measurement model that accounts for different types of noise (see e.g., Boker & Nesselroade, 2002) or by including terms that model perturbations to the system (e.g., Boker & Laurenceau, 2006; Butner et al., 2005).

10.3.2.3 Reservoir Model

Based on the damped linear oscillator, Deboeck and Bergeman (2013) defined the Reservoir Model. It captures the same fluctuations as the damped linear oscillator, but, unlike the latter, takes ceiling and floor effects of measurements into account. The model is based on fluctuations of the water level in a reservoir that is constantly being filled with water (subsequently called the input) while some of the water escapes (subsequently called the output). Depending on the input and output, the water level in the reservoir may change from being high (when input is greater than output) to low (when output is greater than input) to maintaining a stable value in between (when input and output are relatively equal for a certain amount of time). Based on this physical example, the Reservoir Model is defined as (Deboeck & Bergeman, 2013):

$$dy(t) = \beta y(t)\,dt + \varepsilon(t)\,dt$$

where $\beta < 0$ and $\varepsilon(t) \geq 0$. The constraints put on the parameters follow from the derivation of the model, such that β represents the pressure-dependent outflow and $\varepsilon(t)$ represents the inflow. The bigger the outflow, the more easily a buildup of inflow is regulated. To give an example: imagine that during a specific day, stress builds up due to a number of events (i.e., $\varepsilon(t)$ is large). The parameter β then marks the difference between being able to regulate this stress (β is sufficiently large) or having a stress overload (β is too small). Importantly, $\varepsilon(t)$ is itself a function of time, so that the input may change over time: sometimes there is more input (more stressful days) or less input (more relaxing days).

While the model seems promising, it has not yet been applied frequently.

10.3.3 Nonlinear Models

Linear models are a useful tool for investigating affect dynamics. However, evidence suggests that they may fail to capture some fundamental characteristics of affective data, such as V-shaped relationships between variables (e.g., PA-NA; Diener & Iran-Nejad, 1986; Schimmack, 2001; valence-arousal; Kuppens et al., 2012b) and abrupt changes in the temporal dynamics of affect (i.e., phase transitions; Bonsall et al., 2012; Scherer, 2000; Thagard & Nerb, 2002; van de Leemput et al., 2014).

There are several ways to accommodate phenomena that deviate from linear dynamics. First, one may choose to tweak the linear model so that it may be used in specific applications. For example, one may choose to incorporate abrupt changes in the dynamical system by making one or several parameters time- or context-dependent (Boker et al., 2016; Driver & Voelkle, 2018b). These tweaks may seem familiar, as they have also been discussed in the context of nonstationarity (see *Extensions* of *Autoregressive Models*).

Another option is to use *nonlinear* models of affect dynamics. Nonlinear models are models that cannot be rewritten to the form specified in Eq. (10.3). What the nonlinearity looks like, is left to the researcher to decide, and may go from the nonlinear transformation of variables to the inclusion of an interaction term between them. Examples of nonlinear models are

$$d\boldsymbol{y}(t) = \ln(\boldsymbol{y}(t))dt$$
$$d\boldsymbol{y}(t) = \boldsymbol{y}^3(t)dt$$
$$d\boldsymbol{y}(t) = (\boldsymbol{y}(t) + \boldsymbol{y}^2(t))dt$$

and, to pick the concrete example of a damped nonlinear oscillator (Boker & Graham, 1998):

$$\frac{d^2y(t)}{dt^2} = Ey(t) + Z\frac{dy(t)}{dt} + \Theta y^3(t)$$

The difficulty thus lies not in recognizing what nonlinear models are, but in how these models can be used and interpreted, as they often produce very complex behavior with very few parameters. Despite their great appeal, we caution the interested reader in applying nonlinear models to data without considering (a) what behavior the model produces, (b) whether this behavior is interesting with regards to affect dynamics, and (c) whether other, simpler models can be used instead. This is not to say that nonlinear models cannot be applied to affect dynamics; On the contrary, given that nonlinear tendencies are observed in the affective time series of individuals, this calls to the use of these models. However, researchers should also consider the difficulty in identifying a model that produces much of the behavior we see in the literature, a point to which we will return later (Brown et al., 2013; Sussmann & Zahler, 1978).

10.3.3.1 Catastrophe Theory

Originally conceived of by Thom (1975) and then popularized by Zeeman (e.g., Zeeman, 1976), catastrophe theory quickly gained traction in psychology due to the perceived range of problems that it can deal with (e.g., Flay, 1978; Hartelman et al., 1998). In the domain of emotions, it has been explicitly used by Allen and Carifio (1995), included in theory by Scherer (2000) (albeit speculatively, but see also Sacharin et al., 2012; Sander et al., 2005), and alluded to by Frijda (2007).

In its most basic form, catastrophe theory defines a *potential function* that binds together the variables in which one is interested. Then, the model defines the movement in this potential as (Chow et al., 2015):

$$d\boldsymbol{y}(t) = \frac{\partial V(\boldsymbol{y}(t);\boldsymbol{\theta})}{\partial \boldsymbol{y}}dt$$

where $V(\boldsymbol{y}(t);\boldsymbol{\theta})$ is the potential function of $\boldsymbol{y}(t)$, given the parameters inside the parameter vector $\boldsymbol{\theta}$. The symbol ∂ denotes the partial derivative. In this context, this means that for the potential function, the derivative is taken with respect to the variables $\boldsymbol{y}(t)$, so that the parameters $\boldsymbol{\theta}$ are considered to be constant. Because of this, the

$\boldsymbol{y}(t)$ are often taken as the dependent variables (or behavioral variables). The values to which the $\boldsymbol{y}(t)$ are regulated then depend on the values of the control parameters in $\boldsymbol{\theta}$. In practice, these control parameters can themselves be functions of some independent variables, so that

$$\theta = \Omega x$$

where Ω is a diagonal matrix consisting of the different weights of the predictors in $\boldsymbol{x}$.

The challenge of catastrophe theory then lies in the construction of the potential function. Luckily, many such models already exist, the most popular one being the cusp catastrophe model (Chow et al., 2015; Hartelman et al., 1998; Scherer, 2000; Zeeman, 1976). Its potential function and partial derivative are:

$$V\left(y(t);,\alpha;,\beta\right) = \frac{1}{4}y^4(t) - \alpha y(t) - \frac{1}{2}\beta y^2(t)$$

$$\frac{\partial V\left(y(t);,\alpha;,\beta\right)}{\partial y(t)} = y^3(t) - \alpha - \beta y(t)$$

It includes one behavioral variable $y(t)$ and two control parameters α and β. To understand how the control parameters work, we refer the reader to Fig. 10.8—for a visualization on what it implies for the potential function, we refer to Fig. 10.9. The black lines represent lines of attractors, meaning that values of $y(t)$ below or above this line are regulated towards it. Once on the line, the system reaches equilibrium and stops moving. Given that there are no sources of stochasticity, the only way to elicit movements in the behavioral variable $y(t)$ is through changes in the

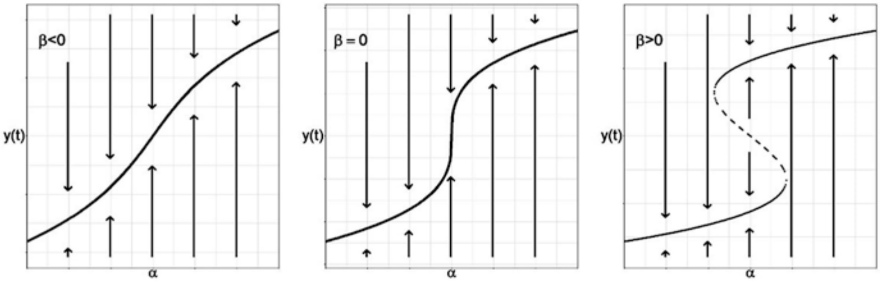


Fig. 10.8 The cusp catastrophe model for different values of α and β. Values of $y(t)$ are regulated towards the solid lines, as indicated by the arrows. Keeping β constant, increasing the value of α goes together with increased values of $y(t)$. When we keep $\beta \leq 0$, increasing the value of α leads to continuous increases in the value to which $y(t)$ is regulated (i.e., the attractor value). When β is greater than 0, a discrete jump in the attractor value can be seen when a certain threshold value of α is exceeded. The emotional state remains on this plane until one decreases the value of α beyond another, separate threshold, a characteristic of the cusp catastrophe model called *hysteresis*. The dotted part in this plot is a line of repellors that can never be reached by the emotional state

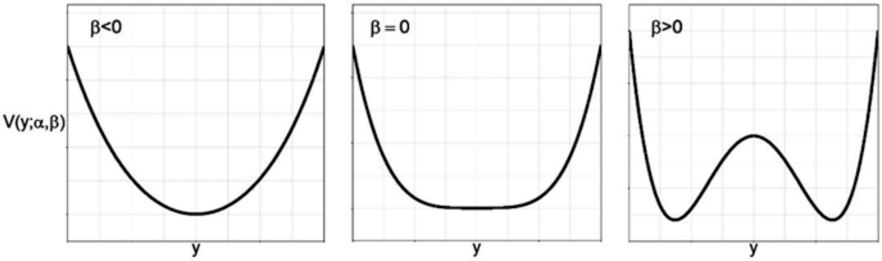


Fig. 10.9 The potential function of the cusp catastrophe model for different values of β, keeping α constant. The affective state $y(t)$ moves towards the local minima of this potential function (i.e., towards the bottom of the wells, which are the attractors), as captured by the differential equation. When β increases, the system goes from having one well or attractor to having two, corresponding to the bifurcation seen in Fig. 10.8

control parameters, which amounts to changes in the predictor variables x. Looking back at the left plot of Fig. 10.8, we can see that increasing the value of α leads to increased values of $y(t)$. But what happens when we increase the value of β? As you can see in the middle and right plot, the potential function creates a fold (a process also known as *bifurcation*; Strogatz, 2018), with a lower region (lower values of $y(t)$), an upper region (higher values of $y(t)$, and a middle region that connects the former two (the dotted line). Note that the middle region consists of repellors, so that $y(t)$ can never be regulated towards it. This implies that $y(t)$ can only be regulated towards the lower and upper region, which produces some interesting behavior.

Imagine that we manipulate α for the higher values of β. Starting out at the lower region and slowly increasing the value of α, we see that $y(t)$ only gradually increases, until suddenly, $y(t)$ shows a discrete jump from the edge of the lower region to the upper region. This behavior is at the heart of why catastrophe theory is popular: Continuous increases in the predictor variables may elicit sudden phase transitions in the dependent variable. Interestingly, decreasing the value of α does not imply a jump back to the lower region at the same threshold as the upwards jump, a characteristic known as *hysteresis*.

To make this a bit more concrete, consider the following example. Take the behavioral variable $y(t)$ to be perceived stress during the day, take the value of α to be dependent on physiological and/or emotional arousal, and the value of β to be dependent on suppression. When an individual does not suppress feelings of arousal, then the cusp catastrophe model would predict that with increases of arousal come continuous increases of perceived stress. With this comes the assumption that when arousal decreases, perceived stress will also decrease in a continuous fashion (as shown in the left plot of Fig. 10.8). Now consider the case when an individual suppresses much of the arousal he/she feels (right plot of Fig. 10.8), then one may initially perceive less stress, up until a critical value at which arousal becomes too high and perceived stress abruptly increases (i.e., suddenly the stress becomes overwhelming). Importantly, due to hysteresis, it will not be easy for the individual to recover from this sudden burst of stress: falling back into the "normal" pattern of stress requires arousal to decrease beyond the previous transition point.

Given our explanation, we hope that the potential of this model is clear. It makes explicit what factors contribute to the creation of the fold (β) and the abrupt change in affect dynamics (α), and how we may attempt to alleviate this state. The model is, however, deterministic in nature, leaving no place to stochastic noise in the system, be it due to internal and external perturbations or due to measurement error. To alleviate this limitation, stochastic versions of catastrophe models have been proposed (see Cobb & Watson, 1980; Wagenmakers et al., 2005).

Despite the frequent use of catastrophe-related terminology in theories of emotion and emotion dynamics, the models themselves have not, to the knowledge of the authors, been directly applied to affect dynamics. It is, however, related to a recently proposed nonlinear model of affect dynamics, to which we turn next.

10.3.3.2 Affective Ising Model

The Affective Ising Model (AIM) is capable of modeling phase transitions, which may occur either due to contextual stimuli or due to random fluctuations (Fig. 10.10). The AIM is a theoretical nonlinear diffusion model that assumes that the emotional life of individuals consists of two pools of binary neurons (i.e., neurons which only have an on- or off-state; Loossens et al., 2020). The state of these two pools determines the amount of PA and NA a person experiences at a given point in time.

Activation in the pools is subject to several forces. More specifically, (a) each neuron has a pool-specific threshold of activation (θ_i) that may be lowered or increased by environmental factors (β_i), and (b) neurons of a given pool that are activated will excite the other neurons of the same pool and inhibit the ones in the other pool (λ_i and λ_{12} respectively).

Instead of describing the time evolution of the binary neurons themselves, the AIM describes the dynamics of the overall activation in the pools. Let y_1 and y_2 denote the average activation of pool 1 (PA) and pool 2 (NA) respectively, then the dynamical equations are given by:

$$dy_1(t) = -\delta \frac{\partial F(y_1(t), y_2(t))}{\partial y_1} dt + \sqrt{2\delta}\, dw_1(t)$$

$$dy_2(t) = -\delta \frac{\partial F(y_1(t), y_2(t))}{\partial y_2} dt + \sqrt{2\delta}\, dw_2(t)$$

where $F(y_1, y_2)$ is defined as:

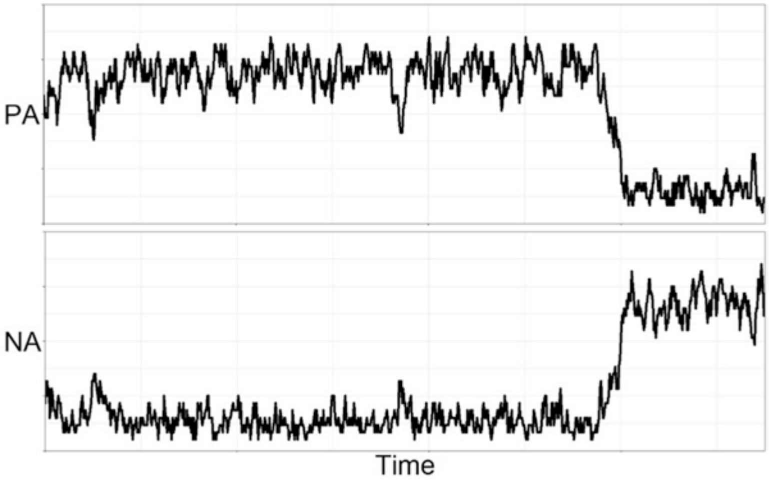


Fig. 10.10 Simulated data of an AIM with two modes. In this figure, it is shown that the AIM can account for discrete shifts in affect dynamics. In this case, the AIM transitions from a high PA-low NA state to a low PA-high NA state

$$F\left(y_1,y_2\right)=\sum_{2}^{i=1}\left(-\lambda_i y_i^2+\left(\theta_i-\beta_i\right)y_i\right)+\lambda_{12}y_1y_2+$$
$$\sum_{2}^{i=1}\nu_i\left(y_i\ln\left(y_i\right)+\left(1-y_i\right)\ln\left(1-y_i\right)\right)$$

where ν_i relates to the number of neurons in a specific pool and δ determines the speed with which the system diffuses towards an equilibrium state (see Loossens et al., 2020 for more on this). The function $F(y_1,y_2)$ is called the *free energy function* and it plays a similar role to the potential function in catastrophe theory models. It can be interpreted as an individual's emotional landscape, through which a the affective state moves. This state will tend towards minima in the landscape (the attractors), but may move upwards due to stochastic fluctuations, so that affect is always evolving.

The AIM induces nonlinearity in two ways. First, it includes logarithmic terms in Eq. (5), making the drift of the AIM nonlinear. Furthermore, the states y_1 and y_2 of the AIM are constrained to fall between 0 (all neurons are inactive) and 1 (all neurons are active), which introduces some boundary effects that are absent in most of the discussed models. As a consequence, the AIM can reproduce some complex phenomena often found in affect dynamics (for some results, see Loossens et al., 2020).

While certainly promising, one clear disadvantage of the model is its limitation to two dimensions (PA and NA), without current alternative to incorporate more than these two dimensions.

10.3.3.3 Chaos

Our discussion of nonlinear models would not be complete without at least braising the topic of *chaos*. Yet, this discussion will stay limited, as chaos has not found its way in affect dynamics despite being used in emotion-related research (e.g., Chow et al., 2016; Fredrickson & Losada, 2005; Losada, 1999).

Chaos refers to deterministic nonlinear systems that are extremely sensitive to initial conditions. With this, we mean that very small differences in a beginning state may lead to large differences in the long run. With this comes another defining feature of chaos, its unpredictable character: Even if there is only small measurement error, your predictions will deviate strongly from the actual behavior of the system. This implies that we can only begin to predict emotional behavior when we are able to measure emotions with no error at all.[7] Consequently, if one decides to use chaotic systems to model affect dynamics, one should also assume that predicting future affect is impossible.

The use of chaotic models in emotion research is limited, and when it has been used, was severely criticized (e.g., Brown et al., 2013; Guastello, 2014 on the studies by Fredrickson & Losada, 2005; Losada, 1999; see also Kellert, 2001). This criticism is primarily directed at the blind use of *fancy* models on data that do not really call for it. For example, Brown et al. (2013) and Guastello (2014) criticized the use of the chaotic Lorenz equations in the studies of Losada (1999) and Fredrickson and Losada (2005), mostly because the latter had no theoretical reasons to use this model in the first place. A same case has also been made for catastrophe theory models, where Sussmann and Zahler (1978) stressed that these models cannot be used on all data that show discrete jumps.

The blind use of such models not only pertains to their predictions, but also to the assumptions that one makes about the underlying process. Chaotic models are deterministic in nature, meaning that no stochasticity is involved at all—neither from inherent randomness of the process nor from unknown internal or external influences on the process. This means that if one is ready to assume such a model is a trustworthy reflection of the emotional system, one also assumes that a select number of variables can be used to describe this system. It seems unlikely that a complex system such as emotions can be described by such a select set of variables, and even if we are ready to assume this, then the question remains whether emotion theorists are comfortable with the notion that emotions evolve in a completely deterministic fashion. We believe few researchers would like to go that far.

---

[7] If this is the case, we are able to predict the emotional behavior of an individual for eternity, as the system is deterministic.

10.3.4 Limitations

Although continuous-time models may provide some solutions to the problems of discrete-time models, they still suffer from a number of limitations. First, many continuous-time models have no closed-form parametric solutions, meaning that they rely on approximate, numerical methods for their estimation. Unfortunately, these methods are very susceptible to local minima in the parameter space, so that the optimal parameter set is not necessarily identified (Myung, 2003). Matters become even worse for nonlinear models, as they often do not even have an analytic solution to their differential equations (e.g., the AIM; Loossens et al., 2020). This means that the solution of the differential equation has to be approximated with numerical integration methods, which may be difficult to implement and very time-consuming (Strogatz, 2018). Given this limitation, it may become clear why their application to psychological research remains limited (Ryan et al., 2018). Often, continuous-time models require the researcher to use specialized software, or construct it themselves, although attempts have been made to make such software more widely available through e.g. R packages that aid in parameter estimation (*ctsem*; Driver et al., 2017; *dynr*; Ou et al., 2019; *OpenMx*; Boker et al., 2020; Hunter, 2018).

Another limitation pertains to the fact that many of the models that were discussed in this section have originally been created to model the behavior of physical systems (Kellert, 2001). Metaphors like “emotions as a thermostat” or “as a reservoir filling with water” may seem to convey some characteristics of emotions, but this may not necessarily be the case. One should realize that these equations have been designed to model a specific, often simple physical system, and may not always be applicable to the complex systems we try to model with them. This is not to say that these models cannot be used for affect dynamics: Instead, it is a reminder that each model may capture a specific aspect of the emotional system, and that at some point, an integration of such models may be needed.

10.4 Conclusion

In this chapter, we provided the reader with a general overview of some of the computational models that try to capture (and explain) affective fluctuations in individuals. Within the scope of this chapter, we discussed discrete-time and continuous-time models, each with their own strengths and limitations. More than providing a general overview of some computational models, we tried to provide the reader with the means to evaluate the use of these models and interpret their results in a more clear-cut way.

As the focus of our chapter was on describing different models of affect dynamics, some of the topics central to computational modeling have been left undiscussed. We will mention some of these topics and refer the reader to the literature to learn more.

10.4.1 Undiscussed Topics

A first undiscussed topic is the one of parameter estimation. While on some occasions we have commented on the reliability or the difficulty of estimation, we have not touched upon the topic of estimation itself. It is, however, an important topic that has led to a rich literature that evaluates different estimation techniques and their reliability. For the discrete-time topics, some interesting references are Lütkepohl (2005), Rojas (1996), and Sutton and Barto (2018), and for continuous-time models, some examples of how they can be estimated come from Driver and Voelkle (2018a), M. Chen et al. (2018), Chow et al. (2015), Chow et al. (2016), Hu et al. (2014), Oravecz et al. (2011), and Oud and Jansen (2000).

Related to this is the topic of state space models (SSM; Hamilton, 1994a; Harvey, 1989). SSM are models that make a distinction between measurements and process, similar to what structural equation models do. However, the former are more appropriate for use in design with ILD, and we therefore leave the latter undiscussed (see Chow et al., 2010 for a comparison between the two). This way, a set of two equations jointly provide a model for the evolution of a dynamical system over time: A measurement equation to model the observations of the variables and a transition equation to model the latent processes. In the context of the models discussed here, the general SSM for a discrete-time model may be formulated as:

$$\begin{aligned} \boldsymbol{y}_t &= \boldsymbol{\tau} + \Lambda \boldsymbol{\eta}_t + \boldsymbol{\varepsilon}_t \\ \boldsymbol{\eta}_t &= \boldsymbol{\alpha} + B\boldsymbol{\eta}_{t-1} + \boldsymbol{\zeta}_t \end{aligned}$$

where the observations and latent process are contained within $\boldsymbol{y}_t$ and $\boldsymbol{\eta}_t$ resp. Importantly, the factor loading matrix Λ relates the observed variables to the underlying latent processes. $\boldsymbol{\tau}$ and $\boldsymbol{\alpha}$ represent the intercepts of measurement and process, and $\boldsymbol{\varepsilon}$ and $\boldsymbol{\zeta}$ are the measurement error and process noise.

Many of the models that have been discussed in this chapter have originally been formulated within the SSM framework (e.g., fmVAR; Adolf et al., 2017), and SSM techniques are often used to aid in parameter estimation (e.g., Kalman filters; M. Chen et al., 2018; Driver & Voelkle, 2018a). We refer the interested reader to Hamilton (1994a) and Harvey (1989) for a more detailed discussion of this framework.

Another important undiscussed topic is that of *model selection*. In the introduction, we briefly mentioned that computational models could be compared to each other regarding model performance, providing evidence for a given model compared to other models. This is an important analytic step, and often says more than just a simple application of one such models to the data. For example, if we use a VAR model to analyze data, we might get small estimates for the crossregressive effects. If we leave it at this, we cannot infer whether these effects contribute much to the model's fit (i.e., whether they are important enough to interpret). To be able to make such an inference, we can analyze the data using a modified VAR model in which all cross-regressive effects are set to zero. If we then find that this second model performs better than the first, we have evidence that no temporal relations between the variables exist (at least not for these data).

Many model selection tools exist, of which we mention only a few. A first popular tool of model selection is *cross-validation*. In cross-validation you use your data to assess the predictive performance of your models (Arlot & Celisse, 2010; Bergmeir et al., 2018; Roberts et al., 2017). In time series research, some related techniques are referred to as *forecasting methods*, in which only past data is used to predict future data, which is not the case for cross-validation (Hyndman et al., 2011; Hyndman & Koehler, 2006; Tashman, 2000). A second, a computationally less expensive model comparison tool is the relative measure of fit, which assesses how well a model fits the data while accounting for the complexity of the model (e.g., AIC and BIC; Bengtsson & Cavanaugh, 2006; Masson, 2011; Schwarz, 1978; Vandekerckhove et al., 2015; Wagenmakers & Farrell, 2004). Third, the parametric bootstrap can be used to simulate data and compare these to the real data with the use of some data-driven statistics (Wehrens et al., 2000). Another interesting way to use the parametric bootstrap is to simulate data starting from different models and check whether the data-generating model is also the model that fits these data best. Using this method, the distinguishability and mimicry of different models can be assessed (Navarro et al., 2004; Wagenmakers et al., 2004).

A final undiscussed topic is the one of individual differences in affect dynamics. All models in this chapter have been formulated to be only applicable to one subject. However, computational models need not be limited to this one case, but may be transformed into a multilevel structure to take into account individual differences (Gelman, 2006; Gelman & Hill, 2006). Some models have already been extended to such a multilevel structure, such as the VAR model (Ariens et al., 2020), the OU model (Driver & Voelkle, 2018a; Oravecz et al., 2011), and the damped linear oscillator (Hu et al., 2014). While very useful, multilevel extensions are not always straightforward and require some additional thought on the modeler's side, often making them difficult to implement.

10.4.2 Final Note

We would like to end this chapter on a final note. While computational models may certainly help progress the affect dynamics field, it is clear that each model suffers from its own limitations. Moreover, computational models are often simplifications of the processes in which we are interested. In light of these limitations, one may become skeptic about their use. To battle this skepticism, we want to remind the reader of another quote of the late Box (1979) (see also Box, 1976, p. 202): "All models are wrong but some are useful."

Appendix 1: Properties of the VAR

Properties of the AR Model

Given the AR model (repeated here):

$$y_j = \delta + \varphi y_{j-1} + \varepsilon_j.$$

we can define some properties of the process. These properties are defined and mathematically derived below.

Predictions. Given a first observation y_0 collected at time t_0, we are able to predict the next measurement y_1, as:

$$\begin{aligned} \langle y_1 \,|\, y_0 \rangle &= \delta + \varphi y_0 + \varepsilon_1 \\ &= \delta + \varphi y_0 \end{aligned}$$

where $\langle \cdot \rangle$ denotes the time-dependent expected value (i.e., $E[.]$). Note that the innovations do not play a role in the expectation of y_1, given that their expected value is equal to 0.

Using the same principle, we can also make predictions about observations further in the future. For instance, the expectation of y_2 conditional on the observation y_0 is given by:

$$\begin{aligned} \langle y_2 \,|\, y_0 \rangle &= \delta + \varphi y_1 \\ &= \delta + \varphi(\delta + \varphi y_0) \\ &= (1+\varphi)\delta + \varphi^2 y_0 \end{aligned}$$

In general, the prediction of a future observation y_j conditional on y_0 is:

$$\langle y_j \,|\, y_0 \rangle = \left(\sum_{k=0}^{j-1} \varphi^k \right) \delta + \varphi^j y_0 \tag{10.7}$$

Baseline. Since the magnitude of φ^j shrinks as j increases, in the long-time limit, it holds that:

$$lim_{j\to\infty} \left(\sum_{j-1}^{k=0} \varphi^k \right) = \frac{1}{1-\varphi}$$

As a result, the predictions $\langle y_j | y_0 \rangle$ converge towards a fixed point:

$$\begin{aligned} lim_{j\to\infty}(\langle y_1 | y_0 \rangle) &= lim_{j\to\infty}\left(\left(\sum_{k=0}^{j-1}\varphi^k\right)\delta + \varphi^j y_0\right) \\ &= \frac{1}{1-\varphi}\delta + 0 \\ &= \frac{\delta}{1-\varphi} \\ &= \mu \end{aligned} \tag{10.8}$$

This fixed point μ can be considered the emotional baseline (i.e., the dotted line in Fig. 10.1) and represents the emotional state to which the emotional state is expected to evolve to. As such coincides with the end state of a regulation process (provided nothing happens to disrupt the regulation process).

It also represents the state that will be visited the most by the individual over longer periods of time. For that reason, it coincides with the mean of the distribution of observations $\{y_j \mid j,\ldots,N\}$ for sufficiently large N. Because of this, the baseline is also referred to as the *stationary mean*. The term stationary is used to stress that the baseline is independent of time.

When an AR(1) process is only observed during a short period of time during which the emotional state is still relaxing (i.e., converging) towards the baseline, then the mean of the observations will differ from the stationary mean. Only when measurements have been collected for a sufficiently long period of time will the mean of the data distribution coincide with the stationary mean.

Uncertainty. Until now, we were only concerned with point-predictions of future observations. However, we can also compute the uncertainty that is associated with these predictions. For this, we realize that the observation y_1 is normally distributed with mean $\delta + \varphi y_0$ (the prediction) and variance σ_ε^2:

$$y_1 \mid y_0 \sim N\left(\delta + \varphi y_0, \sigma_\varepsilon^2\right)$$

Because of stochasticity, uncertainty about predictions typically grows the further in the future you go. It can be shown that the future observation y_j, given observation y_0, is normally distributed with the mean being the point-prediction in Eq. (10.7) and variance given by:

$$\sigma_j^2 = \sum_{j-1}^{k=0} \varphi^{2k}\sigma_\varepsilon^2 \tag{10.9}$$

where in the long-time limit:

$$lim_{j\to\infty}\left(\sum_{j-1}^{k=0}\varphi^{2k}\right) = \frac{1}{1-\varphi^2}$$

so that the variance of the uncertainty distribution in the long-time limit converges to

$$\sigma^2 = \frac{\sigma_\varepsilon^2}{1-\varphi^2} \tag{10.10}$$

Like the stationary mean, this variance is time-independent and thus called the *stationary variance*.

Autocovariance. An AR model relies on the assumption that measurements y_j at time t_j are related to measurements y_{j-1} at time t_{j-1}, i.e. that there is a time-dependence between measurements. The extent to which this relationship holds is expressed by the autocovariance. The autocovariance at lag-p σ_p is defined as:

$$\sigma_p = \left\langle \left(y_{j+p} - \mu\right)\left(y_j - \mu\right)\right\rangle$$

To compute the autocovariance of the AR process, we first reformulate the model in terms of the baseline μ. To do so, we substitute δ for $(1 - \varphi)\mu$ (see Eq. (10.8)) to obtain:

$$\begin{aligned} y_j &= \left(1-\varphi\right)\mu + \varphi y_{j-1} + \varepsilon_j \\ &= \mu - \varphi\mu + \varphi y_{j-1} + \varepsilon_j \end{aligned}$$

Then, by rearranging the terms, we can write

$$y_j - \mu = \varphi\left(y_{j-1} - \mu\right) + \varepsilon_j .$$

Setting the innovations to zero (they do not correlate with anything), we find (see Eq. (10.7))

$$\begin{aligned} \sigma_p &= \left\langle \left(y_{j+p} - \mu\right)\left(y_j - \mu\right)\right\rangle \left(\text{Def.autocovariance}\right) \\ &= \left\langle \varphi^p \left(y_j - \mu\right)\left(y_j - \mu\right)\right\rangle \left(\text{Generalization previous property}\right) \\ &= \left\langle \varphi^p \left(y_j - \mu\right)^2 \right\rangle \\ &= \varphi^p \sigma^2 \end{aligned} \tag{10.11}$$

Here we have used the fact that the centered variable $y_j - \mu$ have the same stationary variance (Eq. (10.10)) as the variable y_j themselves. If we standardize the measurements so that $\sigma^2 = 1$, we obtain the autocorrelation:

$$\rho\left(p\right) = \varphi^p$$

From this expression, it can be seen that the autoregressive coefficient φ of the AR model corresponds to the autocorrelation between measurements at lag 1.

Properties of the VAR Model

We can generalize the properties of the AR model to fit the *d*-dimensional VAR model (repeated here):

$$\boldsymbol{y}_j = \boldsymbol{\delta} + \Phi \boldsymbol{y}_{j-1} + \boldsymbol{\varepsilon}_j$$
$$\boldsymbol{\varepsilon}_j \sim N\left(\mathbf{0}, \Sigma_\varepsilon\right)$$

Predictions. Just like for the AR model, the prediction of a future observation conditional on the observation y_0 is given by (see Eq. (10.7))

$$\left\langle y_j \middle| \mathrm{y}_0 \right\rangle = \left(\sum_{k=0}^{j-1} \Phi^k \right) \boldsymbol{\delta} + \Phi^j \boldsymbol{y}_0 \tag{10.12}$$

Importantly, this equation results in a vector that contains all expectation values for all *d* variables of the model.

Baseline. Using a similar reasoning as for the AR model (see Eq. (10.8)), but this time using matrices instead of scalars, it can be shown that the predictions of the VAR model Eq. (10.12) converge to the baseline:

$$\boldsymbol{\mu} = \left(I_d - \Phi \right)^{-1} \boldsymbol{\delta}$$

where I_d is the *d*-dimensional identity matrix.

Uncertainty. An expression similar to Eq. (10.9) can be obtained for the growing uncertainty of the VAR model:

$$\Sigma_j = \sum_{j-1}^{k=0} \Phi^k \Sigma_\varepsilon \left(\Phi^k \right)^T$$

For stable transition matrices Φ, this covariance matrix becomes constant in the long-time limit. This stationary covariance is given by

$$\Sigma = \sum_{\infty}^{k=0} \Phi^k \Sigma_\varepsilon \left(\Phi^k \right)^T$$

and is a solution of the discrete-time Lyapunov equation

$$\Sigma - \Phi \Sigma \Phi^T = \Sigma_\varepsilon$$

Given the transition matrix Φ and the covariance Σ_ε of the innovations, this Lyapunov equation enables us to compute the stationary covariance without having to compute an infinite sum.

Autocovariance. The autocovariance of the VAR model is similar to the autocovariance of the AR (see Eq. (10.11), namely

$$\begin{aligned} \Sigma_p &= \left\langle \left(y_{j+p} - \mu\right)\left(y_j - \mu\right)^T \right\rangle \\ &= \Phi^p \Sigma \end{aligned}$$

Appendix 2: Autocorrelation of Bivariate VAR

If we take a bivariate VAR model with the intercepts $\boldsymbol{\delta} = \mathbf{0}$, then we can compute the autocovariance as:

$$\begin{aligned} \sigma_{tt-1} &= \left(y_{1t} y_{1t-1}\right) \\ &= \left(\delta_1 + \varphi_{11} y_{1t-1} + \varphi_{12} y_{2t-1} + \varepsilon_{1t}\right) y_{1t-1} \\ &= \delta_1 y_{1t-1} + \varphi_{11} y_{1t-1}^2 + \varphi_{12} y_{2t-1} y_{1t-1} + \varepsilon_{1t} \\ &= \delta_1 y_{1t-1} + \varphi_{11} y_{1t-1}^2 + \varphi_{12} y_{2t-1} y_{1t-1} + \varepsilon_{1t} \\ &= 0 + \varphi_{11} \sigma_1^2 + \varphi_{12} \sigma_{12} + 0 \\ &= \varphi_{11} \sigma_1^2 + \varphi_{12} \sigma_{12} \end{aligned}$$

We can compute the autocorrelation as:

$$\begin{aligned} \rho_{tt-1} &= \frac{\sigma_{tt-1}}{\sigma_{1t} \sigma_{1t-1}} \\ &= \frac{\sigma_{tt-1}}{\sigma_1^2} \\ &= \frac{\varphi_{11} \sigma_1^2 + \varphi_{12} \sigma_{12}}{\sigma_1^2} \\ &= \varphi_{11} + \frac{\varphi_{12} \sigma_{12}}{\sigma_1^2} \end{aligned}$$

More generally, it holds that for a variable y_i:

$$\begin{aligned}\sigma_{tt-1} &= y_{it}y_{it-1}\\ &= \left(\delta_i + \varphi_{ii}y_{it-1} + \sum_{\substack{i'=1\\ i'\neq i}}^{d}\varphi_{ii'}y_{i't-1} + \varepsilon_{it}\right)y_{it-1}\\ &= \varphi_{ii}\sigma_i^2 + \sum_{\substack{i'=1\\ i'\neq i}}^{d}\varphi_{ii'}\sigma_{ii'}\end{aligned}$$

and:

$$\rho_{tt-1} = \varphi_{ii} + \sum_{d}^{\substack{i'=1\\ i'\neq i}}\frac{\varphi_{ii'}\sigma_{ii'}}{\sigma_i^2}$$

References

Adolf, J. K., Voelkle, M. C., Brose, A., & Schmiedek, F. (2017). Capturing context-related change in emotional dynamics via fixed-moderated time series analysis. *Multivariate Behavioral Research, 52*, 499–531. https://doi.org/10.1080/00273171.2017.1321978

Albers, C. J., & Bringmann, L. F. (2020). Inspecting gradual and abrupt changes in emotion dynamics with the time-varying change point autoregressive model. *European Journal of Psychological Assessment, 36*, 492–499. https://doi.org/10.1027/1015-5759/a000589

Allen, B. D., & Carifio, J. (1995). Nonlinear analysis: Catastrophe theory modeling and Cobb's Cusp Surface Analysis Program. *Evaluation Review, 19*, 64–83. https://doi.org/10.1177/0193841X9501900103

Ariens, S., Ceulemans, E., & Adolf, J. K. (2020). Time series analysis of intensive longitudinal data in psychosomatic research: A methodological overview. *Journal of Psychosomatic Research, 137*, 110191.

Arlot, S., & Celisse, A. (2010). A survey of cross-validation procedures for model selection. *Statistics Surveys, 4*, 40–79. https://doi.org/10.1214/09-SS054

Bengtsson, T., & Cavanaugh, J. E. (2006). An improved Akaike information criterion for state-space model selection. *Computational Statistics & Data Analysis, 50*, 2635–2654. https://doi.org/10.1016/j.csda.2005.05.003

Bennett, D., Davidson, G., & Niv, Y. (2020). A model of mood as integrated advantage. Retrieved from https://10.31234/osf.io/dzsme

Bennett, D., & Niv, Y. (2018, June 7). Opening Burton's clock: Psychiatric insights from computational cognitive models. Retrieved from https://10.31234/osf.io/y2vzu

Bergmeir, C., Hyndman, R. J., & Koo, B. (2018). A note on the validity of cross-validation for evaluating autoregressive time series prediction. *Computational Statistics & Data Analysis, 120*, 70–83. https://doi.org/10.1016/j.csda.2017.11.003

Bergstrom, A. R. (1984). Continuous-time stochastic models and issues of aggregation over time. In Z. Griliches & M. D. Intriligator (Eds.), *Handbook of econometrics*. Elsevier Science.

Boker, S. M. (2002). Consequences of continuity: The hunt for intrinsic properties within parameters of dynamics in psychological processes. *Multivariate Behavioral Research, 37*, 405–422. https://doi.org/10.1207/S15327906MBR3703_5

Boker, S. M., & Graham, J. (1998). A dynamical systems analysis of adolescent substance abuse. *Multivariate Behavioral Research, 33*, 479–507. https://doi.org/10.1207/s15327906mbr3304_3

Boker, S. M., & Laurenceau, J.-P. (2006). Dynamical systems modeling: An application to the regulation of intimacy and disclosure in marriage. In T. A. Walls & J. L. Schafer (Eds.), *Models for intensive longitudinal data*. Oxford University Press.

Boker, S. M., & Nesselroade, J. R. (2002). A method for modeling the intrinsic dynamics of intraindividual variability: Recovering the parameters of simulated oscillators in multi-wave panel data. *Multivariate Behavioral Research, 37*, 127–160. https://doi.org/10.1207/S15327906MBR3701_06

Boker, S. M., Staples, A. D., & Hu, Y. (2016). Dynamics of change and change in dynamics. *Journal of Person-Oriented Research, 2*, 34–55. https://doi.org/10.17505/jpor.2016.05

Boker, S. M., Neale, M. C., Maes, H. H., Wilde, M. J., Spiegel, M., Brick, T. R., Estabrook, R., Bates, T. C., Mehta, P., von Oertzen, T., Gore, R. J., Hunter, M. D., Hackett, D. C., Karch, J., Brandmaier, A. M., Pritikin, J. N., Zahery, M., Kirkpatrick, R. M., Wang, Y., et al. (2020). OpenMx 2.17.4 user guide.

Bolger, N., Davis, A., & Rafaeli, E. (2003). Diary methods: Capturing life as it is lived. *Annual Review of Psychology, 54*, 579–616. https://doi.org/10.1146/annurev.psych.54.101601.145030

Bonsall, M. B., Wallace-Hadrill, S. M. A., Geddes, J. R., Goodwin, G. M., & Holmes, E. A. (2012). Nonlinear time-series approaches in characterizing mood stability and mood instability in bipolar disorder. *Proceedings of the Royal Society B, 279*, 916–924. https://doi.org/10.1098/rspb.2011.1246

Booij, S. H., Wigman, J. T. W., Jacobs, N., Thiery, E., Derom, C., Wichers, M., & Oravecz, Z. (2020). Cortisol dynamics in depression: Application of a continuous-time process model. *Psychoneuroendocrinology, 115*. https://doi.org/10.1016/j.psyneuen.2020.104598

Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology, 9*, 91–121. https://doi.org/10.1146/annurev-clinpsy-050212-185608

Borsboom, D., Cramer, A. O. J., Schmittmann, V. D., Epskamp, S., & Waldorp, L. J. (2011). The small world of psychopathology. *PLoS One, 6*, e27407. https://doi.org/10.1371/journal.pone.0027407

Box, G. E. P. (1976). Science and statistics. *Journal of the American Statistical Association, 71*, 791–799.

Box, G. E. P. (1979). Robustness in the strategy of scientific model building. In R. L. Launer & G. N. Wilkinson (Eds.), *Robustness in statistics*. Academic.

Box, G. E. P. (1966). Use and abuse of regression. *Technometrics, 8*(4), 625–629.

Box, G. E. P., & Jenkins, G. M. (1970). *Time series analysis: Forecasting and control*. Holden-Day.

Breiman, L. (2001). Statistical modeling: The two cultures. *Statistical Science, 16*, 199–231.

Brickman, P., & Campbell, D. T. (1971). Hedonic relativism and planning the good society. In M. H. Appley (Ed.), *Adaptation-level theory*. United States of America, Academic Press.

Bringmann, L. F., Ferrer, E., Hamaker, E. L., Borsboom, D., & Tuerlinckx, F. (2018). Modeling nonstationary emotion dynamics in dyads using a time-varying vetor-autoregressive model. *Multivariate Behavioral Research, 53*, 293–314. https://doi.org/10.1080/00273171.2018.1439722

Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., Borsboom, D., & Tuerlinckx, F. (2013). A network approach to psychopathology: New insights into clinical longitudinal data. *PLoS One, 8*, e60188. https://doi.org/10.1371/journal.pone.0060188

Brown, N. J. L., Sokal, A. D., & Friedman, H. L. (2013). The complex dynamics of wishful thinking: The critical positivity ratio. *American Psychologist, 68*, 801–813. https://doi.org/10.1037/a0032850

Bulteel, K., Tuerlinckx, F., Brose, A., & Ceulemans, E. (2016). Using raw var regression coefficients to build networks can be misleading. *Multivariate Behavioral Research, 51*, 330–344. https://doi.org/10.1080/00273171.2016.1150151

Butner, J., Amazeen, P. G., & Mulvey, G. M. (2005). Multilevel modeling of two cyclical processes: Extending differential structural equation modeling to nonlinear coupled systems. *Psychological Methods, 10*, 159–177. https://doi.org/10.1037/1082-989X.10.2.159

Cabrieto, J., Adolf, J., Tuerlinckx, F., Kuppens, P., & Ceulemans, E. (2018). Detecting long-lived autodependency changes in a multivariate system via change point detection and regime switching models. *Scientific Reports, 8*. https://doi.org/10.1038/s41598-018-33819-8

Chen, M., Chow, S.-M., & Hunter, M. D. (2018). Stochastic differential equation models with timevarying parameters. In K. van Montfort, J. H. L. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences*.

Chen, Y., & Zhang, S. (2020). A latent Gaussian process model for analysing intensive longitudinal data. *The British Journal of Mathematical and Statistical Psychology, 73*, 237–260. https://doi.org/10.1111/bmsp.12180

Chow, S.-M., Lu, Z., & Zhu, H. (2016). Fitting nonlinear ordinary differential equation models with random effects and unknown initial conditions using the stochastic approximation expectation maximization (SAEM) algorithm. *Psychometrika, 81*, 102–134. https://doi.org/10.1007/s11336-014-9431-z

Chow, S.-M., Ram, N., Boker, S. M., Fujita, F., & Clore, G. (2005). Emotion as a thermostat: Representing emotion regulation using a damped oscillator model. *Emotion, 5*, 208–225. https://doi.org/10.1037/1528-3542-5.2.208

Chow, S.-M., Witkiewitz, K., Grasman, R. P. P. P., & Maisto, S. A. (2015). The cusp catastrophe model as cross-sectional longitudinal mixture structural equation model. *Psychological Methods, 20*, 142–164. https://doi.org/10.1037/a0038962

Chow, S.-M., Ho, M.-H. R., Hamaker, E. L., & Dolan, C. V. (2010). Equivalence and differences between structural equation modeling and state-space modeling techniques. *Structural Equation Modeling, 17*(2), 303–332.

Cobb, L., & Watson, B. (1980). Statistical catastrophe theory: An overview. *Mathematical Modelling, 1*, 311–317.

Congard, A., Dauvier, B., Antoine, P., & Gilles, P.-Y. (2011). Integrating personality, daily life events and emotion: Role of anxiety and positive affect in emotion regulation dynamics. *Journal of Research in Personality, 45*, 372–384. https://doi.org/10.1016/j.jrp.2011.04.004

Cunningham, W. A., Dunfield, K. A., & Stillman, P. E. (2013). Emotional states from affective dynamics. *Emotion Review, 5*, 344–355. https://doi.org/10.1177/1754073913489749

Daros, A. R., Daniel, K. E., Boukhechba, M., Chow, P. I., Barnes, L. E., & Teachman, B. A. (2019). Relationship between trait emotion dysregulation and emotional experiences in daily life: An experience sampling study. *Cognition and Emotion, 34*, 743–755. https://doi.org/10.1080/02699931.2019.1681364

de Haan-Rietdijk, S., Voelkle, M. C., Keijsers, L., & Hamaker, E. L. (2017). Discrete-vs. continuous time modeling of unequally spaced experience sampling method data. *Frontiers in Psychology, 8*, 1849.

Deboeck, P. R. (2013). Dynamical systems and models of continuous time. In T. D. Little (Ed.), *The Oxford handbook of quantitative methods in psychology*. Oxford University Press.

Deboeck, P. R., & Bergeman, C. S. (2013). The reservoir model: A differential equation model of psychological regulation. *Psychological Methods, 18*, 237–256. https://doi.org/10.1037/a0031603

Deboeck, P. R., & Preacher, K. J. (2016). No need to be discrete: A method for continuous time mediation analysis. *Structural Equation Modeling: A Multidisciplinary Journal, 23*, 61–75. https://doi.org/10.1080/10705511.2014.973960

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*(366a), 427–431.

Diener, E., & Iran-Nejad, A. (1986). The relationship in experience between various types of affect. *Journal of Personality and Social Psychology, 50*, 1031–1038.

Doll, B. B., Simon, D. A., & Daw, N. D. (2012). The ubiquity of model-based reinforcement learning. *Current Opinion in Neurobiology, 22*, 1075–1081. https://doi.org/10.1016/j.conb.2012.08.003

Driver, C. C., Oud, J. H. L., & Voelkle, M. C. (2017). Continuous time structural equation modeling with R package ctsem. *Journal of Statistical Software, 77*. https://doi.org/10.18637/jss.v077.i05

Driver, C. C., & Voelkle, M. C. (2018a). Hierarchical Bayesian continuous time dynamic modeling. *Psychological Methods, 23*, 774–799. https://doi.org/10.1037/met0000168

Driver, C. C., & Voelkle, M. C. (2018b). Understanding the time course of interventions with continuoustime dynamic models. In K. van Montfort, J. H. L. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences*.

Dunn, E. C., Nishimi, K., Gomez, S. H., Powers Lott, A., & Bradley, B. (2018). Developmental timing of trauma exposure and emotion dysregulation in adulthood: Are there sensitive periods when trauma is most harmful? *Journal of Affective Disorders, 227*, 869–877. https://doi.org/10.1016/j.jad.2017.10.045

Ekman, P. (1992). An argument for basic emotions. *Cognition and Emotion, 6*, 169–200.

Eldar, E., & Niv, Y. (2015). Interaction between emotional state and learning underlies mood instability. *Nature Communications, 6*. https://doi.org/10.1038/ncomms7149

Eldar, E., Rutledge, R. B., Dolan, R. J., & Niv, Y. (2015). Mood as representation of momentum. *Trends in Cognitive Sciences, 20*, 15–24. https://doi.org/10.1016/j.tics.2015.07.010

Epskamp, S. (2020a). Psychometric network models from time series and panel data. *Psychometrika, 85*, 206–231. https://doi.org/10.1007/s11336-020-09697-3

Epskamp, S., Waldorp, L. J., Mottus, R., & Borsboom, D. (2018). The Gaussian graphical model in cross-sectional and time-series data. *Multivariate Behavioral Research, 53*, 453–480. https://doi.org/10.1080/00273171.2018.1454823

Epskamp, S. (2020b). graphicalVAR: Graphical VAR for experience sampling data. R package version 0.2.4. Retrieved from https://CRAN.R-project.org/package=graphicalVAR

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software, 48*(4), 1–18.

Farrell, S., & Lewandowsky, S. (2010). Computational models as aids to better reasoning in psychology. *Current Directions in Psychological Science, 19*, 329–335. https://doi.org/10.1177/0963721410386677

Feldman Barrett, L. (2009). Variety is the spice of life: A psychological construction approach to understanding variability in emotion. *Cognition and Emotion, 23*, 1284–1306. https://doi.org/10.1080/02699930902985894

Flay, B. R. (1978). Catastrophe theory in social psychology: Some applications to attitudes and social behavior. *Behavioral Science, 23*, 335–350.

Fredrickson, B. L., & Losada, M. F. (2005). Positive affect and the complex dynamics of human flourishing. *American Psychologist, 60*, 678–686. https://doi.org/10.1037/0003-066X.60.7.678

Fried, E. I., van Borkulo, C. D., Cramer, A. O. J., Boschloo, L., Schoevers, R. A., & Borsboom, D. (2017). Mental disorders as networks of problems: A review of recent insights. *Social Psychiatry and Psychiatric Epidemiology, 52*, 1–10. https://doi.org/10.1007/s00127-016-1319-z

Frijda, N. H. (2007). *The laws of emotion*. Routledge.

Gelman, A. (2006). Multilevel (hierarchical) modeling: What it can and cannot do. *Technometrics, 48*, 432–435. https://doi.org/10.1198/004017005000000661

Gelman, A., & Hill, J. (2006). *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.

Greene, T., Gelkopf, M., Fried, E. I., Robinaugh, D. J., & Pickman, L. L. (2020). Dynamic network analysis of negative emotions and DSM-5 posttraumatic stress disorder symptom clusters during conflict. *Journal of Traumatic Stress, 33*, 72–83. https://doi.org/10.1002/jts.22433

Groen, R. N., Ryan, O., Wigman, J. T. W., Riese, H., Penninx, B. W. J. H., Giltay, E. J., Wichers, M., & Hartman, C. A. (2020). Comorbidity between depression and anxiety: Assessing the role of bridge mental states in dynamic psychological networks. *BMC Medicine, 18*. https://doi.org/10.1186/s12916-020-01738-z

Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological Inquiry, 26*, 1–26. https://doi.org/10.1080/1047840X.2014.940781

Guastello, S. J. (2014). Nonlinear dynamical models in psychology are widespread and testable. *American Psychologist, 69*, 628–629. https://doi.org/10.1037/a0036980

Guthier, C., Dormann, C., & Voelkle, M. C. (2020). Reciprocal effects between job stressors and burnout: A continuous-time meta-analysis of longitudinal studies. *Psychological Bulletin, 146*, 1146–1173. https://doi.org/10.1037/bul0000304

Hamaker, E. L., Ceulemans, E., Grasman, R. P. P. P., & Tuerlinckx, F. (2015). Modeling affect dynamics: State of the art and future challenges. *Emotion Review, 7*, 316–322. https://doi.org/10.1177/1754073915590619

Hamaker, E. L., & Wichers, M. (2017). No time like the present: Discovering the hidden dynamics in intensive longitudinal data. *Current Directions in Psychological Science, 26*, 10–15. https://doi.org/10.1177/0963721416666518

Hamilton, J. D. (1994a). State-space models. In R. F. Engle & D. L. McFadden (Eds.), *Handbook of econometrics*. Elsevier. https://doi.org/10.1016/S15734412(05)80019-4

Hamilton, J. D. (1994b). Time series analysis (Vol. 2). Princeton University Press.

Hamilton, J. D. (2010). Regime switching models. In S. N. Durlauf & L. E. Blume (Eds.), *Macroeconometrics and time series analysis*. Springer.

Hartelman, P. A. I., van der Maas, H. L. J., & Molenaar, P. C. M. (1998). Detecting and modelling developmental transitions. *British Journal of Developmental Psychology, 16*, 97–122.

Harvey, A. C. (1989). *Forecasting, structural time series models and the Kalman filter*. Cambridge university press.

Hektner, M. J., Schmidt, A. J., & Csikszentmihalyi, M. (2006). *Experience sampling methods: Measuring the quality of everyday life* (1st ed.). SAGE Publications.

Hu, Y., Boker, S., Neale, M., & Klump, K. L. (2014). Coupled latent differential equations with moderators: Simulation and application. *Psychological Methods, 19*, 56–71. https://doi.org/10.1037/a0032476

Hunter, M. D. (2018). State space modeling in an open source, modular, structural equation modeling environment. *Structural Equation Modeling, 25*, 307–324. https://doi.org/10.1080/10705511.2017.1369354

Hyndman, R. J., Ahmed, R. A., Athanasopoulos, G., & Shang, H. L. (2011). Optimal combination forecasts for hierarchical time series. *Computational Statistics and Data Analysis, 55*, 2579–2589. https://doi.org/10.1016/j.csda.2011.03.006

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting, 22*, 679–688. https://doi.org/10.1016/j.ijforecast.2006.03.001

Jekel, M. (2019). Empirical content as a criterion for evaluating models. *Cognitive Processing, 20*, 273–275. https://doi.org/10.1007/s10339-019-00913-2

Kellert, S. H. (2001). Extrascientific uses of physics: The case of nonlinear dynamics and legal theory. *Philosophy of Science, 68*, S455–S466.

Koopmans, M. (2011). Epilogue: Psychology at the edge of chaos. In S. J. Guastello, M. Koopmans, & D. Pincus (Eds.), *Chaos and complexity in psychology: The theory of nonlinear dynamical systems*. Cambridge University Press.

Kruis, J., & Maris, G. (2016). Three representations of the Ising model. *Scientific Reports, 6*. https://doi.org/10.1038/srep34175

Kuppens, P., Champagne, D., & Tuerlinckx, F. (2012a). The dynamic interplay between appraisals and core affect in daily life. *Frontiers in Psychology, 3*. https://doi.org/10.3389/fpsyg.2012.00380

Kuppens, P., Oravecz, Z., & Tuerlinckx, F. (2010). Feelings change: Accounting for individual differences in the temporal dynamics of affect. *Journal of Personality and Social Psychology, 99*, 1042–1060. https://doi.org/10.1037/a0020962

Kuppens, P., Tuerlinckx, F., Russell, J. A., & Feldman-Barrett, L. (2012b). The relation between valence and arousal in subjective experience. *Psychological Bulletin, 139*, 917–940. https://doi.org/10.1037/a0030811

Kuppens, P., & Verduyn, P. (2015). Looking at emotion regulation through the window of emotion dynamics. *Psychological Inquiry, 26*, 72–79. https://doi.org/10.1080/1047840X.2015.960505

Kuppens, P., & Verduyn, P. (2017). Emotion dynamics. *Current Opinion in Psychology, 17*, 22–26. https://doi.org/10.1016/j.copsyc.2017.06.004

Kuranova, A., Booij, S. H., Menne-Lothmann, C., Decoster, J., van Winkel, R., Delespaul, P., De Hert, M., Derom, C., Thiery, E., Rutten, B. P. F., Jacobs, N., van Os, J., Wigman, J. T. W., & Wichers, M. (2020). Measuring resilience prospectively as the speed of affect recovery in daily life: A complex systems perspective on mental health. *BMC Medicine, 18*. https://doi.org/10.1186/s12916-020-1500-9

Larsen, R. J., Augustine, A. A., & Prizmic, Z. (2009). A process approach to emotion and personality: Using time as a facet of data. *Cognition and Emotion, 23*, 1407–1426. https://doi.org/10.1080/02699930902851302

Larson, R., & Csikszentmihalyi, M. (1983). The experience sampling method. In H. T. Reis (Ed.), *New directions for methodology of social and behavioral sciences* (Vol. 15). Jossey-Bass.

Loossens, T., Mestdagh, M., Dejonckheere, E., Kuppens, P., Tuerlinckx, F., & Verdonck, S. (2020). The affective ising model: A computational account of human affect dynamics. *PLoS Computational Biology, 16*, e1007860. https://doi.org/10.1371/journal.pcbi.1007860

Loossens, T., Dejonckheere, E., Tuerlinckx, F., Verdonck, S. (2021). Informing VAR(1) with qualitative dynamical features improves predictive accuracy. Psychological Methods.

Losada, M. (1999). The complex dynamics of high performance teams. *Mathematical and Computer Modelling, 30*, 179–192. https://doi.org/10.1016/S0895-7177(99)00189-2

Luce, R. D. (1995). Four tensions concerning mathematical modeling in psychology. *Annual Review of Psychology, 46*, 1–26.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer.

Lütkepohl, H., & Xu, F. (2012). The role of the log transformation in forecasting economic variables. *Empirical Economics, 42*(3), 619–638.

Mason, L., Eldar, E., & Rutledge, R. B. (2017). Mood instability and reward dysregulation—A neurocomputational model of bipolar disorder. *JAMA Psychiatry, 74*, 1275–1276.

Masson, M. E. J. (2011). A tutorial on a practical Bayesian alternative to null-hypothesis significance testing. *Behavioral Research Methods, 43*, 679–690. https://doi.org/10.3758/s13428-0100049-5

Moors, A., & Fischer, M. (2019). Demystifying the role of emotion in behavior: Toward a goal-directed account. *Cognition & Emotion, 33*, 94–100. https://doi.org/10.1080/02699931.2018.1510381

Myin-Germeys, I., Kasanova, Z., Vaessen, T., Vachon, H., Kirtley, O., Viechtbauer, W., & Reininghaus, U. (2018). Experience sampling methodology in mental health research: New insights and technical developments. *World Psychiatry, 17*, 123–132. https://doi.org/10.1002/wps.20513

Myung, J. (2003). Tutorial on maximum likelihood estimation. *Journal of Mathematical Psychology, 47*, 90–100. https://doi.org/10.1016/S0022-2496(02)00028-7

Navarro, D. J., Pitt, M. A., & Myung, I. J. (2004). Assessing the distinguishability of models and the informativeness of data. *Cognitive Psychology, 49*, 47–84. https://doi.org/10.1016/j.cogpsych.11011.001

Nelson, B., McGorry, P. D., Wichers, M., Wigman, J. T. W., & Hartmann, J. A. (2017). Moving from static to dynamic models of the onset of mental disorder: A review. *JAMA Psychiatry, 74*, 528–534. https://doi.org/10.1001/jamapsychiatry.2017.0001

Oravecz, Z., & Brick, T. R. (2019). Associations between slow- and fast-timescale indicators of emotional functioning. *Social Psychological and Personality Science, 10*, 864–873. https://doi.org/10.1177/1948550618797128

Oravecz, Z., Tuerlinckx, F., & Vandekerckhove, J. (2011). A hierarchical latent stochastic differential equation model for affective dynamics. *Psychological Methods, 16*, 468–490. https://doi.org/10.1037/a0024375

Oravecz, Z., Wood, J., & Ram, N. (2018). On fitting a continuous-time stochastic process model in the Bayesian framework. In K. van Monfort, J. H. L. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences*. Springer.

Ou, L., Hunter, M. D., & Chow, S.-M. (2019). What's for dynr: A package for linear and nonlinear dynamic modeling in R. *The R Journal, 11*. https://doi.org/10.32614/RJ-2019-012

Oud, J. H. L. (2007). Continuous time modeling of reciprocal relationships in the cross-lagged panel design. In S. M. Boker & M. J. Wenger (Eds.), *Notre dame series on quantitative methodology: Data analytic techniques for dynamical systems*. Lawrence Erlbaum Associates Publishers.

Oud, J. H. L., & Jansen, R. A. R. G. (2000). Continuous time state space modeling of panel data by means of SEM. *Psychometrika, 65*, 199–215. https://doi.org/10.1007/BF02294374

Pellert, M., Schweighofer, S., & Garcia, D. (2020). The individual dynamics of affective expressions on social media. *EPJ Data Science, 9*. https://doi.org/10.1140/epjds/s13688-019-0219-3

Popper, K. (1959). *The logic of scientific discovery*. Routledge.

Reed, R. G., Barnard, K., & Butler, E. A. (2015). Distinguishing emotional coregulation from codysregulation: An investigation of emotional dynamics and body weight in romantic couples. *Emotion, 15*(1), 45–60. https://doi.org/10.1037/a0038561

Rindskopf, D. (1984). Using phantom and imaginary latent variables to parameterize constraints in linear structural models. *Psychometrika, 49*(1), 37–47.

Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Arroita, G., Hauenstein, S., LahozMonfort, J. J., Schröder, B., Thuiller, W., Warton, D. I., Wintle, B. A., Hartig, F., & Dormann, C. F. (2017). Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography, 40*, 913–929. https://doi.org/10.1111/ecog.02881

Rojas, R. (1996). *Neural networks: A systematic introduction*. Springer.

Rutledge, R. B., Moutoussis, M., Smittenaar, P., Zeidman, P., Taylor, T., Hrynkiewicz, L., Lam, J., Skandali, N., Siegel, J. Z., Ousdal, O. T., Prabhu, G., Dayan, P., Fonagy, P., & Dolan, R. J. (2017). Association of neural and emotional impacts of reward prediction errors with major depression. *JAMA Psychiatry, 74*, 790–797. https://doi.org/10.1001/jamapsychiatry.2017.1713

Rutledge, R. B., Skandali, N., Dayan, P., & Dolan, R. J. (2014). A computational and neural model of momentary subjective well-being. *Proceedings of the National Academy of Sciences, 111*(33), 12252–12257. https://doi.org/10.1073/pnas.1407535111

Ryan, O., Kuiper, R. M., & Hamaker, E. L. (2018). A continuous time approach to intensive longitudinal data: What, why, and how? In K. van Montfort, J. H. L. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences*. Springer.

Sacharin, V., Sander, D., & Scherer, K. R. (2012). The perception of changing emotion expressions. *Cognition & Emotion, 26*, 1273–1300. https://doi.org/10.1080/02699931.2012.656583

Sander, D., Grandjean, D., & Scherer, K. R. (2005). A systems approach to appraisal mechanisms in emotion. *Neural Networks, 18*, 317–352. https://doi.org/10.1016/j.neunet.2005.03.001

Santangelo, P. S., Limberger, M. F., Stiglmayr, C., Houben, M., Coosemans, J., Verleysen, G., Kuppens, P., Tuerlinckx, F., Vanpaemel, W., & Ebner-Priemer, U. W. (2016). Analyzing subcomponents of affective dysregulation in borderline personality disorder in comparison to other clinical groups using multiple e-diary datasets. *Borderline Personality Disorder and Emotion Dysregulation, 3*, 5. https://doi.org/10.1186/s40479-016-0039-z

Scargle, J. D. (1981). Studies in astronomical time series analysis: Modeling random processes in the time domain. *Astrophysical Journal Supplement Series, 45*, 1–71.

Scherer, K. R. (2000). Emotions as episodes of subsystem synchronization driven by nonlinear appraisal processes. In M. Lewis & I. Granic (Eds.), *Emotion, development, and self-organization: Dynamic systems approaches to emotional development (Cambridge Studies in Social and Emotional Development)*. Cambridge University Press. https://doi.org/10.1017/CBO9780511527883.005

Scherer, K. R. (2005). What are emotions? And how can they be measured? *Social Science Information, 44*, 695–729. https://doi.org/10.1177/0539018405058216

Schimmack, U. (2001). Pleasure, displeasure, and mixed feelings: Are semantic opposites mutually exclusive? *Cognition and Emotion, 15*, 81–97. https://doi.org/10.1080/02699930126097

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6*, 461–464.

Schweitzer, F., & Garcia, D. (2010). An agent based model of collective emotions in online communities. *The European Physical Journal, 77*, 533–545. https://doi.org/10.1140/epjb/e2010-00292-1

Seeley, S. H., Garcia, E., & Mennina, D. S. (2015). Recent advances in laboratory assessment of emotion regulation. *Current Opinion in Psychology, 3*, 58–63. https://doi.org/10.1016/j.copsyc.2015.02.009

Smaldino, P. E. (2017). Models are stupid, and we need more of them. In R. R. Vallacher, S. J. Read, & A. Nowak (Eds.), *Computational social psychology*. Routledge.

Smith, K. E., Crosby, R. D., Wonderlich, S. A., Forbush, K. T., Mason, T. B., & Moessner, M. (2018). Network analysis: An innovative framework for understanding eating disorder psychopathology. *International Journal of Eating Disorders, 51*, 214–222. https://doi.org/10.1002/eat.22836

Steele, J. S., & Ferrer, E. (2011). Latent differential equation modeling of self-regulatory and coregulatory affective processes. *Multivariate Behavioral Research, 46*, 956–984. https://doi.org/10.1080/00273171.2011.625305

Steele, J. S., Gonzales, J. E., & Ferrer, E. (2018). Uses and limitations of continuous-time models to examine dyadic interactions. In K. van Montfort, J. H. L. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences*.

Strogatz, S. (2018). *Nonlinear dynamics and chaos: With applications to physics, biology, chemistry, and engineering*. CRC Press.

Sussmann, H. J., & Zahler, R. S. (1978). A critique of applied catastrophe theory in the behavioral sciences. *Behavioral Science, 23*, 383–389.

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT Press.

Tashman, L. J. (2000). Out-of-sample tests of forecasting accuracy: An analysis and review. *International Journal of Forecasting, 16*, 437–450.

Thagard, P., & Nerb, J. (2002). Emotional gestalts: Appraisal, change, and the dynamics of affect. *Personality and Social Psychology Review, 6*, 274–282.

Thom, R. (1975). *Structural stability and morphogenesis* (D. H. Fowler, Trans.) [(Original work published in 1972)]. W. A. Benjamin.

Tong, H. (2011). Threshold models in time series analysis—30 years on. *Statistics and its Interface, 4*(2), 107–118.

Uhlenbeck, G. E., & Ornstein, L. S. (1930). On the theory of Brownian motion. *Physical Review, 46*, 823–841.

van de Leemput, I. A., Wichers, M., Cramer, A. O. J., Borsboom, D., Tuerlinckx, F., Kuppens, P., van Nes, E. H., Viechtbauer, W., Giltay, E. J., Aggen, S. H., Derom, C., Jacobs, N., Kendler, K. S., van der Maas, H. L. J., Neale, M. C., Peeters, F., Thiery, E., Zachar, P., & Scheffer, M. (2014). Critical slowing down as early warning for the onset and termination of depression. *Proceedings of the National Academy of Sciences, 111*, 87–92. https://doi.org/10.1073/pnas.1312114110

Vandekerckhove, J., Matzke, D., & Wagenmakers, E.-J. (2015). Model comparison and the principle of parsimony. In J. R. Busemeyer, Z. Whang, J. T. Townsend, & A. Eidels (Eds.), *The Oxford handbook of computational and mathematical psychology*. Oxford University Press.

Vanhasbroeck, N., Devos, L., Pessers, S., Kuppens, P., Vanpaemel, W., Moors, A., & Tuerlinckx, F. (2021). Testing a computational model of subjective well-being: A preregistered replication of Rutledge et al. (2014). *Cognition and Emotion, 35*(4), 822–835. https://doi.org/10.1080/02699931.2021.1891863.

Velicer, W. F., & Molenaar, P. C. (2012). Time series analysis for psychological research. In *Handbook of psychology, second edition*. Society. https://doi.org/10.1002/9781118133880.hop202022

Verduyn, P., Van Mechelen, I., Tuerlinckx, F., Meers, K., & Van Coillie, H. (2009). Intensity profiles of emotional experience over time. *Cognition and Emotion, 23*, 1427–1443. https://doi.org/10.1080/02699930902949031

Villano, W. J., Otto, A. R., Ezie, C. E. C., Gillis, R., & Heller, A. S. (2020). Temporal dynamics of real world emotions are more strongly linked to prediction error than outcome. *Journal of Experimental Psychology: General, 149*, 1755–1766. https://doi.org/10.1037/xge0000740

Vinckier, F., Rigoux, L., Oudiette, D., & Pessiglione, M. (2018). Neuro-computational account of how mood fluctuations arise and affect decision-making. *Nature Communications, 9*. https://doi.org/10.1038/s41467-018-03774-z

Voelkle, M. C., Ebner, N. C., Lindenberger, U., & Riediger, M. (2013). Here we go again: Anticipatory and reactive mood responses to recurring unpleasant situations throughout adulthood. *Emotion, 13*, 424–433. https://doi.org/10.1037/a0031351

Voelkle, M. C., & Oud, J. H. L. (2013). Continuous time modelling with individually varying time intervals for oscillating and non-oscillating processes. *British Journal of Mathematical and Statistical Psychology, 66*, 103–126. https://doi.org/10.1111/j.2044-8317.2012.02043.x

Wagenmakers, E.-J., & Farrell, S. (2004). AIC model selection using Akaike weights. *Psychonomic Bulletin & Review, 11*, 192–196.

Wagenmakers, E.-J., Molenaar, P. C. M., Grasman, R. P. P. P., Hartelman, P. A. I., & van der Maas, H. L. J. (2005). Transformation invariant stochastic catastrophe theory. *Physica D, 211*, 263–276. https://doi.org/10.1016/j.physd.2005.08.014

Wagenmakers, E.-J., Ratcliff, R., Gomez, P., & Iverson, G. J. (2004). Assessing model mimicry using the parametric bootstrap. *Journal of Mathematical Psychology, 48*, 28–50. https://doi.org/10.1016/j.jmp.2003.11.004

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature, 393*, 440–442.

Wehrens, R., Putter, H., & Buydens, L. M. C. (2000). The bootstrap: A tutorial. *Chemometrics and Intelligent Laboratory Systems, 54*, 35–52.

Wichers, M., Smit, A. C., & Snippe, E. (2020). Early warning signals based on momentary affect dynamics can expose nearby transitions in depression: A confirmatory single-subject time-series study. *Journal for Person-Oriented Research, 6*, 1–15. https://doi.org/10.17505/jpor.2020.22042

Wood, J., Oravecz, Z., Vogel, N., Benson, L., Chow, S.-M., Cole, P., Conroy, D. E., Pincus, A. L., & Ram, N. (2018). Modeling intraindividual dynamics using stochastic differential equations: Age differences in affect regulation. *Journal of Gerontology: Psychological Sciences, 73*, 171–184. https://doi.org/10.1093/geronb/gbx013

Zeeman, E. C. (1976). Catastophe theory. *Scientific American, 234*, 65–83. https://doi.org/10.1038/scientificamerican0476-65

Chapter 11
Flexibility and Adaptivity of Emotion Regulation: From Contextual Dynamics to Adaptation and Control

Nimat Ullah, Jan Treur, and Sander L. Koole

Abstract To effectively regulate their emotions, people have to continually adjust their emotion regulation strategies to changes in internal and external demands. Flexibility and adaptivity are thus vital to emotion regulation. Flexibility refers to the context-sensitive deployment of emotion regulation strategies while regulating one's own emotions. By contrast, adaptivity refers to the changes in such context-sensitive deployment of strategies that take place while regulating one's own emotions over time, and the control of such change processes. Flexibility is increased by having larger repertoire of strategies as this increases the odds that an appropriate strategy is available. On the other hand, having more emotion regulation strategies to choose from creates the need for decision. Because this decision-making process occurs in real time, it requires emotional stability and cognitive analysis. Over time, different experiences in choosing emotion regulation strategies give rise to learning which is one form of adaptivity. Flexibility in emotion regulation is provoked by the fluctuating contexts, whereas adaptations are induced by the frequency and intensity of emotion-regulatory activities. These adaptations are grounded in changes at a cellular and molecular level. The latter adaptations are often referred to by the term plasticity, or first-order adaptation. Often some form of control is applied to such adaptation processes, determining when and under which circumstances the adaptations should take place; this is often referred to by the term meta-plasticity or second-order adaptation. The above concepts are illustrated by simulated example scenarios based on different computational network models. In the first simulated scenario, a varying context shows the flexibility in the choice of emotion regulation strategies. In the second and third scenario, plasticity and meta-plasticity are illustrated based on first- and second-order adaptive network models.

N. Ullah · J. Treur (✉)
Social AI Group, Department of Computer Science, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands
e-mail: j.treur@vu.nl

S. L. Koole
Amsterdam Emotion Regulation Lab, Department of Clinical Psychology, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands
e-mail: s.l.koole@vu.nl

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_11

11.1 Introduction

People use a wide variety of strategies in regulating their emotions (Koole, 2009; Gross, 1998; Parkinson & Totterdell, 1999). The efficacy of these emotion-regulation strategies employed by a person depends on the (person-specific and external) circumstances in which the strategies are employed. As such, the question arises how people are able to flexibly adapt their use of emotion regulation strategies to shifting situational demands; see also (Aldao et al., 2015). Consider, for instance, the following scenario: You are an office worker who feels hurt every time his colleagues criticize him. To regulate your emotions, you have various options: Walking away, distracting yourself, hiding your reaction, or mentally distancing yourself from your colleagues. Which of these options is optimal depends on the situation. For instance, if the critical colleague is your manager, then walking away is probably not advisable. Alternatively, if the critical colleague is your best friend, then mental distancing may hurt your friendship. Each emotion regulation strategy employed by a person can thus have different results and implications in different (person-specific and external) situations (Aldao, 2013). This is why it is fortunate that people have the capability to flexibility choose between various emotion regulation strategies as per demands of the (both person-specific and external) situation. This capacity is referred to as emotion regulation flexibility (Aldao et al., 2015; Bonanno & Burton, 2013a).

Aside from the flexibility in choice of emotion regulation strategies as per demand of the context, another type of change in the choice of emotion regulation strategies has now been quite extensively discussed in the cognitive, neuro and social sciences (Carstensen et al., 1999). Emotion regulation is a specific form of mental process, like any mental process grounded in the underlying neural mechanisms. In a wider context, according to the neurocognitive science literature, *synaptic* plasticity forms the biological basis for many forms of adaptation (Hebb, 1949); this actually is a form of first-order adaptation. Furthermore, many studies have reported systematic changes in synaptic plasticity that imply a form of control over the plasticity; this has been called *metaplasticity (*Abraham*,* 2008*;* Abraham & Bear*,* 1996*)* and represents a form of second-order adaptation.

Plasticity and metaplasticity in addition to the base dynamics lead to rather complex and usually circular processes, which makes it a challenge to model them computationally. To address such a challenge, recently in the field of Network Science and Artificial Intelligence a suitable Network-Oriented Modeling method based on self-modeling networks has been introduced (Treur, 2019, 2020a). Using this modeling approach a base network is can be extended into a multi-level adaptive network model by adding self-models to it for some of its network characteristics. A first-order self-model can be used to represents first-order adaptation or plasticity and a second-order self-model to represent second-order adaptation or metaplasticity. This has been applied in particular to emotion regulation in (Ullah et al., 2020a). These levels or orders of adaptation can still go higher if the phenomenon itself needs it, for instance (Ullah & Treur, 2020a) presents a fourth-order adaptive network model.

In the remainder of this chapter, we develop computational models of flexibility and adaptivity in emotion regulation. In Sect. 11.2, we start by analyzing the dynamics for contextual flexibility in emotion regulation, In Sect. 11.3, we take a closer look at first-order adaptation in emotion regulation, In Sect. 11.4, we turn to higher-order adaptation and metaplasticity in emotion regulation. Finally, we summarize our main conclusion in Sect. 11.5, and provide references and appendices respectively.

11.2 Dynamics for Contextual Flexibility in Emotion Regulation

11.2.1 Contextual Flexibility in Emotion Regulation

Emotion regulation theorists have distinguished between five families (or broad categories) of emotion regulation strategy (Gross, 1998, 2015; Richards & Gross, 2000). The first family of emotion regulation strategies is to change the kind of situation one is in. For instance, the office worker from Sect. 11.1 can choose to walk outside the office. The second family of emotion regulation strategies focuses on modifying aspects of the situation. For instance, our office worker could hang a ‘do not disturb’ sign by his door to keep the critical colleague at bay. The third family of emotion regulation strategies focuses on changing where one attends. For instance, our office worker could distract himself by mentally planning dinner. The fourth family of emotion regulation strategies consists of changing the interpretation of the situation. For instance, our office worker could tell himself that the critical colleague really means well. Finally, the fifth family of emotion regulation strategies consists of modulating one’s outward emotional responses. For instance, our office worker could actively try to smile to the critical colleague, even while stewing with anger inside.

Initially, emotion regulation researchers assumed that some families of emotion regulation strategies are generally more effective than others. For instance, cognitive change strategies were believed to be more effective than response modulation strategies (Gross, 2001). However, subsequent research revealed that general differences in effectiveness between emotion regulation strategies are small (Aldao & Nolen-Hoeksema, 2012). Moreover, even cognitive change strategies like reappraisal, that are generally effective, may have disadvantages in certain situations (Ford & Troy, 2019). Conversely, there are situations where the use of a response modulation strategy like expressive suppression can prove quite adaptive (Dworkin et al., 2019). Effective emotion regulation thus appears to be not so much a matter of using some strategies and avoiding others. Instead, effective emotion regulation is a matter of finding the right strategy for the situation. This means that flexibly adapting emotion regulation to situational demands plays a vital role in emotion regulation (Aldao, 2013; Gross, 2015; Bonanno & Burton, 2013b; Sheppes, 2014; Webb et al., 2012a).

Empirical research on emotion regulation flexibility has so far been limited. This is one of the reasons why previous work (Sheppes et al., 2011) and our own previous computational model of emotion regulation flexibility (Ullah et al., 2018) that was mainly based on that, only focused on the choice between attention deployment and reappraisal. Going beyond this work, however, this section of the chapter illustrates flexibility by a simulated scenario that involves flexibility among four emotion regulation strategies as per demand of the context.

11.2.2 Simulated Scenarios for Contextual Flexibility in Emotion Regulation

The simulated scenarios presented in this section illustrate the ability to respond to four different situations with different regulation strategies. First, in Sect. 11.2.2.1 the computational network used is briefly explained, next, in Sect. 11.2.2.2 the four simulated scenarios are shown.

11.2.2.1 The Computational Network Model for Contextual Flexibility

Figure 11.1 presents the connectivity of the network model used, with its nomenclature in Table 11.1.

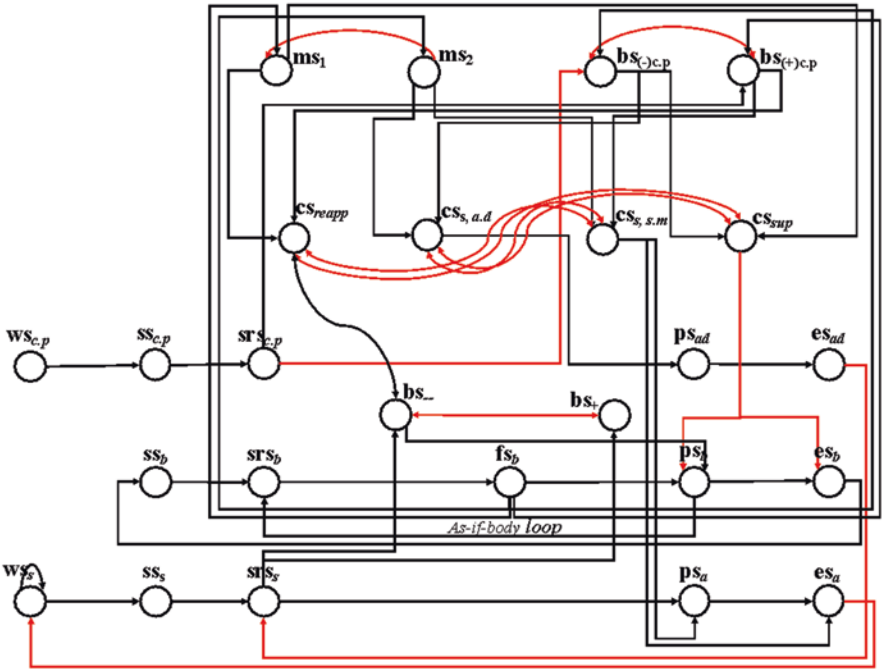


Fig. 11.1 Connectivity of the computational network model used for flexibility; here the red connections are suppressing connections: they have a negative weight (see also Table 11.7 in Appendix 1)

Table 11.1 Nomenclature of the states of the network model used

States	Informal name	Description
ws_s	World state for stimulus s	The situation in the real world that triggers emotion
$\mathrm{ws}_{c.p}$	World state for context pressure	A real-world situation which decides expression of emotion
ss_s	Sensor state for stimulus s	Sensor state for the stimulus s in the real world
$\mathrm{ss}_{c.p}$	Sensor state for context pressure	Senses state for context pressure
ss_b	Sensor state for body	Sensor state for body state b relating to a negative emotion
srs_s	Sensory representation state for stimulus s	Internal representation of the emotion triggering situation
$\mathrm{srs}_{c.p}$	Sensory rep: state for context pressure	Internal representation of the context pressure in the real world
srs_b	Sensory representation state for body	Internal body representation state for b relating to a negative emotion
bs_-	Negative believe state	The negative believe that the person has about something/someone
bs_+	Positive believe state	The positive believe that the person has about something/someone
ms_1	Monitoring state for low emotion level	Monitors for low emotions
ms_2	Monitoring state for high emotion level	Monitors for high emotions
$\mathrm{bs}_{(+)\mathrm{c.p}}$	Belief state for context pressure	Believing that expression of emotion will matter in the environment
$\mathrm{bs}_{(-)\mathrm{c.p}}$	Belief state for context pressure	Believing that expression of emotion won’t matter in the environment
cs_{reapp}	Control state for reappraisal	Controlling negative beliefs about something/someone
$\mathrm{cs}_{s,a.d}$	Control state for attention deployment	Control state for Attention Deployment
$\mathrm{cs}_{s,s.m}$	Control state for situation modification	Control state for situation modification as a result of context
cs_{sup}	Control state for suppression	Control state for Suppression of Expression
fs_b	Feeling state for body state b	Feeling associated to body state b; this is a negative feeling
ps_a	Preparation state for action a	Preparing for action a
ps_b	Preparation for body state b	Preparation state for body state b relating to a negative emotion
ps_{ad}	Preparation state for attention deployment	Preparation for the Attention deployment action
es_a	Execution state for action a	Execution station for action a
es_b	Execution state for body state b	Execution state for body state b, bodily expressing a negative emotion
es_{ad}	Execution state for attention deployment	Execution state for the Attentional Deployment action

Table 11.2 Choice of strategies under high/low intensity of emotions and +/− belief about context pressure

Flexibility parameters		Repertoire of strategies			
Emotion strength	Context pressure (CP)	Situation modification	Attention deployment	Cognitive reappraisal	Expressive suppression
+	+	✓			
+	−		✓		
−	+			✓	
−	−				✓

The computational network model used here inherits flexibility in emotion regulation strategies from (Ullah et al., 2018) and decision-making from (Manzoor et al., 2017). In this model, the phenomenon of emotional arousal and its regulation has been modeled. The emotion eliciting stimulus is taking place as the world state ws_s which activates sensor state ss_s and sensor representation state srs_s. Based on the internal valuation and prior beliefs about the stimulus, the person's feelings gets activated and keeps increasing as a result of internal as-if-body-loop as explained by Damasio (Bechara et al., 2003). On the basis of the intensity of emotions monitored by the monitoring state ms_1 and ms_2, i.e., low and high intensity of emotions, respectively, are activated which then activates the respective control state cs for strategy (cs_{reapp}, $cs_{s.\,a.\,d}$, $cs_{s.\,s.\,m}$, and cs_{sup}) as represented in Table 11.2 below. Empirically, these models can be verified against the literature as described above, representing how specific areas in the brain are casually activated and involved in the generation and regulation of emotions. For instance, the amygdala and prefrontal cortex are the main brain regions involved in this process of emotion generation, valuation of stimulus and regulation of emotions. However, without extensively going into all technical details of the model, the connectivity picture in Fig. 11.1 can be understood as a causal diagram where it is indicated which state is causally affected by which other states. The considered model presented in Fig. 11.1, has the capability to switch between four different strategies (with control states cs_{reapp}, $cs_{s.\,a.\,d}$, $cs_{s.\,s.\,m}$, and cs_{sup}), depending on the situational aspect combinations as shown in Table 11.2. An extensive overview of the modeling approach from (Treur, 2020a, 2016), used for the network model can be found in Appendix 1.

The first column, in Table 11.2, represents the intensity of the emotions: high (+) or low (−). The second column represents the belief about the context pressure during the emotion eliciting situation. This is a kind of prediction for the environment where the (+) means presence of a context factor due to which the expression of emotions can have negative consequences and (−) refers to a context where expression of emotions doesn't matter.

11.2.2.2 Four Simulated Example Scenarios Addressed for Contextual Flexibility

For the four simulated scenarios, the following basic setup is considered

> “An employee A feels angry every time a particular obnoxious coworker B starts talking. Next week the organization has a monthly meeting where presence of all employees is mandatory unless emergency, and where the boss may or may not show up. Employee A doesn’t want anyone, especially his boss to come to know about his attitude towards employee B. Employee A has four options to handle the situation, all depending upon the combination of his intensity of emotions and the chances of presences or absence of their boss at the working place as shown in Table 11.2.”

All values for the network characteristics used for the model are given in Table 11.6 and 11.7 in Appendix 2; they qualitatively validate the model used against the findings from empirically founded literature that serve as qualitative evaluation indicators. These values are essential for the reproduction of the model; they provide the simulation results as shown in Figs. 11.2, 11.3, 11.4, and 11.5. All simulation graphs only display the most essential states for the explanation of the scenario.

Figure 11.2 depicts a scenario for low (−) intensity of emotions and positive (+) belief about CP; this combination triggers the negative belief state bs_{-} and (potentially) in turn the negative emotional response preparation ps_b and by the as-if body loop also the negative feeling state fs_b and due to that the control state for reappraisal cs_{reapp}. The figure also demonstrates the way reappraisal works. As reappraisal alters the interpretation of the stimuli, this can be seen in the figure where initially the negative belief bs_{-} gets quite high but it starts decreasing as soon as the control state for reappraisal cs_{reapp} gets activated. This control state cs_{reapp} takes care of altering the interpretation of the stimuli: by suppressing the negative belief bs_{-}, in turn the positive belief bs_{+} increases which (cyclically) again additionally

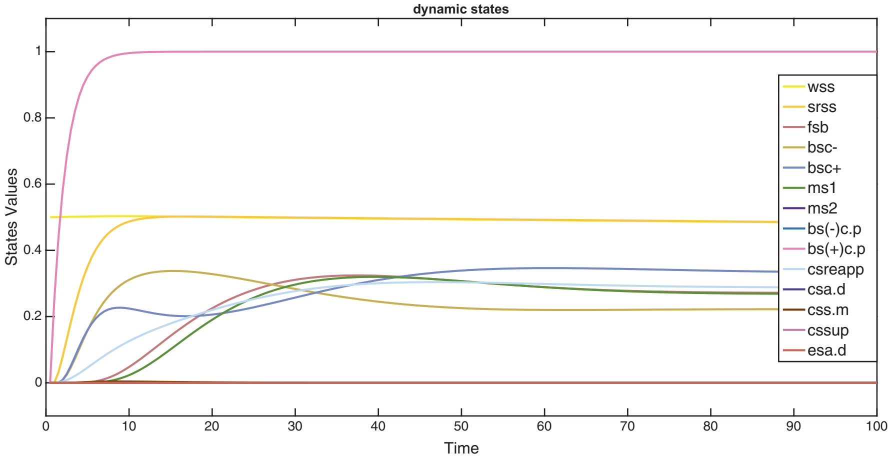


Fig. 11.2 Reappraisal: low intensity negative emotions with context pressure

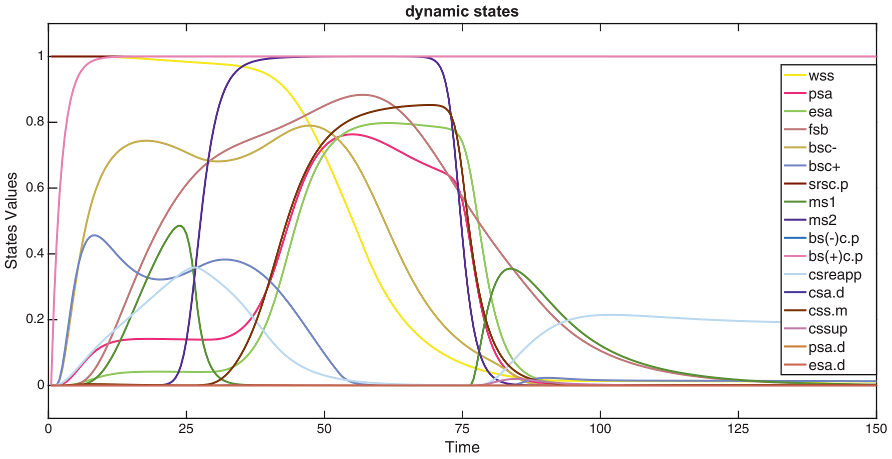


Fig. 11.3 Situation modification: high intensity negative emotions with context pressure

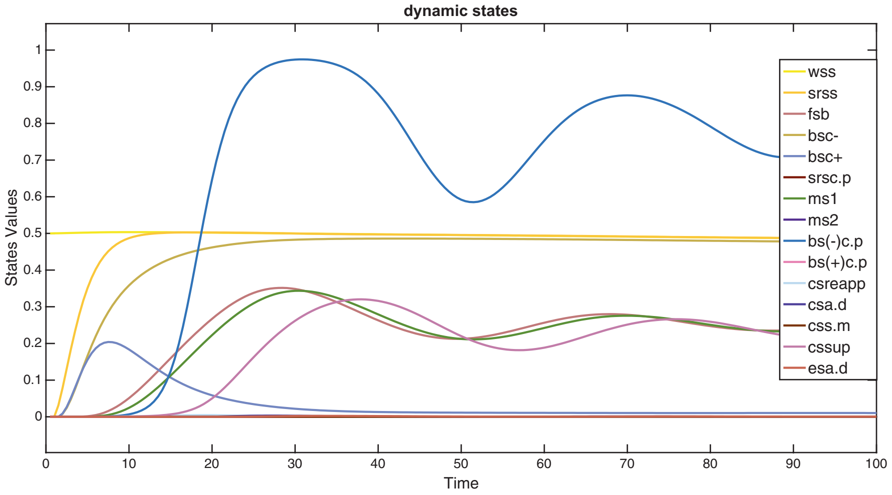


Fig. 11.4 Expressive suppression: low intensity negative emotions with no context pressure

suppresses the negative belief bs_-, as a result of which the preparation for the negative emotional response ps_b and in turn (by the as-if body loop) the negative feeling state fs_b also decrease.

In Fig. 11.3, a context with high (+) intensity of emotions and positive (+) belief about CP is shown which activates situation modification $cs_{s.\,m}$ as an emotion regulation strategy. Here the context pressure motivates the person to hide his emotions. In case of a development of a high intensity of negative emotions, the emotion level starts from 0 after which it gradually goes to low and to high. Therefore, in Fig. 11.3 initially the regulation starts for a combination with low emotion as demonstrated in Fig. 11.2. Later on, as the negative emotions get higher than the low emotions range, the control state for situation modification $cs_{s.\,m}$ gets activated. Situation

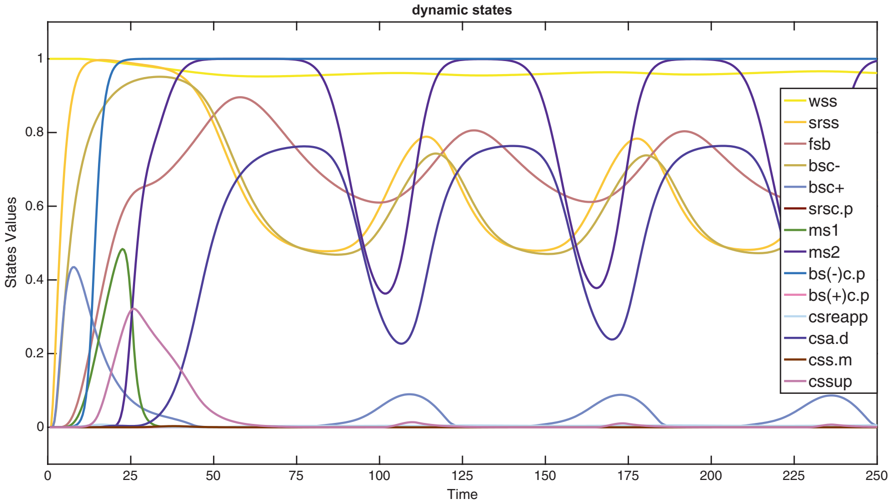


Fig. 11.5 Attention deployment: high intensity negative emotions with no context pressure

modification as a strategy means modifying/leaving the emotional situation, i.e., the world state ws_s for the stimulus. Therefore, it can be observed in the figure that the world state ws_s starts decreasing as soon as the preparation ps_a for the appropriate physical action *a* (e.g., changing position or walking away) and execution es_a of this physical action takes place. This means the person has somehow left the emotional situation and, therefore, his negative emotions also decrease. While emotions of the person are decreasing, this gets into the low emotional zone once again. Therefore, in the figure it can be seen that in that situation reappraisal gets activated accordingly, like in the scenario of Fig. 11.2.

As highlighted in Table 11.2, the combination of low (−) intensity of emotion and negative (−) belief about CP which means no context pressure, activates expressive suppression cs_{sup}. In Fig. 11.4 it can be observed that initially negative feeling state fs_b increases as the negative belief bs_- increases. The increase stops as soon as the control state for suppression cs_{sup} gets activated which suppresses the negative emotional response preparation ps_b and execution es_b which in turn (by the as-if body loop) induces less negative feelings.

As suppression only suppresses the preparation and expression of the emotions and does not affect the causes of the emotional response, the sensor representation state srs_s and negative belief state bs_- for the negative interpretation still remain high, which by many is considered an unhealthy and stressful internal state.

Figure 11.5 represents a context with high (+) intensity of emotions and negative (−) belief about CP, which means that the person can afford it if his emotions are seen by others. This activates attention deployment $cs_{a.d}$ as a main strategy for emotion regulation. This context also has two strategies to deal with just as described in Fig. 11.3. Initially, when the emotions are yet to get high, the person tries to suppress his emoting by using expressive suppression cs_{sup}. Later on, as the emotions get high enough, the person tries to downregulate his emotions by using attention deployment $cs_{a.d}$ where he distracts his attention.

11.3 Plasticity in Emotion Regulation

11.3.1 Adapting how to regulate emotions over time

By flexibly regulating their emotions, people adapt their emotion regulation to different situations. Given that recurring situations are likely to give rise to similar emotion regulation strategies, the person is likely to display certain predictable patterns in emotion regulation patterns. These patterns, in turn, may give rise to long-term adaptations in emotion regulation. These long-term adaptations are captured by the notion of synaptic plasticity.

Synaptic plasticity provides a main neurochemical foundation to learning and memory formation. It refers to the ability of the connections between neurons to get stronger or weaker over time. A synapse refers to the structure that enables an electrical or chemical signal to pass from one neuron to another neuron or a target effector cell. This increase or decrease in the strength of synapse depends upon the neurons' current or recent activation. This has been formulated by Donald Hebb (Hebb, 1949), p. 62, as:

> 'When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased'.

This process, which has become widely known as Hebbian learning. But note that in the above quote Hebb does not call it learning; it only describes changes in 'one or both cells' over time. Sometimes it is summarized in a simplified form as 'neurons that fire together, wire together'. Hebbian learning entails that simultaneous activation of the neurons/cells strengthens the synapses between those two neurons/cells. This is a biological basis for learning. In terms of emotions and specifically emotion regulation, (Giuliani et al., 2011) has studied excessive employment of expressive suppression and brain structures such as in the anterior insula and has come up with positive relation between them. It has been found, for example, that the volume of anterior insula increases as a result of more use of expressive suppression for emotion regulation. Similarly, (Ostroumov & Dani, 2018) provides an extensive review on neuronal plasticity and metaplasticity as a result of stress, nicotine and alcohol. Moreover, reward-driven and prediction-driven synaptic plasticity and hence learning has been explained in (Schultz et al., 1997). In terms of computational modeling, various examples of adaptive computational models can also be found, for instance in (Ullah & Treur, 2019) reward based learning has been demonstrated based on a Hebbian learning process. Similarly, (Zegerius & Treur, 2020) models the working of Eye Movement Desensitization and Reprocessing (EMDR) therapy for persons affected by a Post-Traumatic Stress Disorder (PTSD) by a therapy-induced Hebbian learning process.

Particularly relevant to plasticity of emotion regulation are (Zimmermann & Iwanski, 2014) differences in emotion regulation strategies between young and older adults. The 'Strength and vulnerability integration theory' (Charles, 2010) provides a reason for this shift by stating that it becomes more difficult for an older person to apply response-focused strategies due to less physiological flexibility for higher age. Some other studies agree to these finding and come up with strategies focused findings, for instance, (John & Gross, 2004; Charles & Carstensen, 2007) associate more use of reappraisal at an older age. Moreover, studies like (Lawton et al., 1992; Phillips et al., 2006), also consider older people to be better in controlling emotional situations and quicker in regaining positive mood as compared to the younger adults (Carstensen et al., 2000; Larcom & Isaacowitz, 2009). Furthermore, (Yeung et al., 2011) attributes this retention of positive mood in older people to reappraisal being used as an adaptive emotion regulation strategy. In contrast to suppression, some studies also consider reappraisal more helpful in decreasing psychological distress (Haga et al., 2009; John & Gross, 2004). In case of expressive suppression, even successful suppression doesn't ensure decrease in distress (Gross et al., 1997) but younger adults still would use suppression, maybe because they prefer confrontational coping (Folkman et al., 1987). Similarly, there are various studies which support the notion of increased use of reappraisal by older people and more use of suppression by younger people subject to various possible reasons like the availability of physiological resources, motivational goals, priority given to the emotional wellbeing (Nakagawa et al., 2017; Scheibe & Blanchard-Fields, 2009; Scheibe & Carstensen, 2010; Cutuli, 2014).

Although individual differences do matter for all these changes (Rothbart et al., 2000), there appear to be developmental changes in regulatory capabilities in the later half of adult life. In line with these concepts, according to plasticity (Labouvie-Vief et al., 1989), improvement in cognitive reappraisal as a strategy is essential for maturity in cognition and, therefore, as compared to younger people, older people display more cognitive maturity (Labouvie-Vief & Blanchard-Fields, 1982). Similarly, goal adjustment flexibility is stronger in older persons (Heckhausen & Schulz, 1995; Brandtstädter & Renner, 1990).

Note that all these phenomena that seem to have correlations to age, do not have any causal relation to a notion of age, as age by itself does not cause anything. Such correlations are an emerging result of adaptive processes based on underlying mechanisms where the actual causal relations and pathways can be found. These mechanisms will be discussed in some detail in the current and next section.

11.3.2 Simulated Scenarios for Plasticity in Emotion Regulation

The simulated scenarios presented in this section illustrate the ability to adapt the choice of emotion regulation strategies over time. The differences in emotion regulation strategies for different ages as discussed above will be used for this. First, in Sect. 11.3.2.1 the first-order adaptive computational network used is briefly explained, next, in Sect. 11.3.2.2 a simulated scenario is shown.

11.3.2.1 A First-Order Adaptive Network Model for Plasticity in Emotion Regulation

This section introduces the first-order adaptive network model used for the simulated scenario. The connectivity of the adaptive network model is shown in Fig. 11.6 with an overview of its states in Table 11.3. This first-order adaptive network model, models plasticity of the choice of emotion regulation strategies. Here, the base network models the basic functioning of two well-known emotion regulation strategies: cognitive reappraisal and expressive suppression.

In the base model, as in the model in the previous section, the world state ws_s represent the stimulus in the world that triggers some kind of emotions after the basic processing of the stimulus, i.e., through sensor ss_s, sensor representation state srs_s, and valuation of the stimulus that is the belief of the person about the stimulus. On the basis of beliefs, i.e., bs_- or bs_+ about the stimulus the internal as-if-body-loop of the person gets activated which slowly and gradually increases the feelings of the person that can be positive as well as negative, but here the focus is on negative feelings represented by fs_b. The control state for reappraisal cs_{reapp} represents cognitive reappraisal which regulates emotions by changing one's belief or interpretation for the stimulus. Control state cs_{sup} represents expressive suppression which suppression expression of emotions.

State ms_{dstrss} represents the monitoring state for distress, which according to the literature should remain high if a person is suppressing his/her emotions and should remain low if a person is reappraising his/her emotions.

The self-model modeled in the upper (blue) plane addressing the first-order adaptation, represents the Hebbian learning principle described in Sect. 11.3.1. This adaptation process takes place over the entire life span of an individual. The person uses suppression during the first phase of his life and then switches to reappraisal in the later phase of his life, based on his activations of strategies. This is an emergent effect of the mechanism of Hebbian learning: simultaneous activations of the

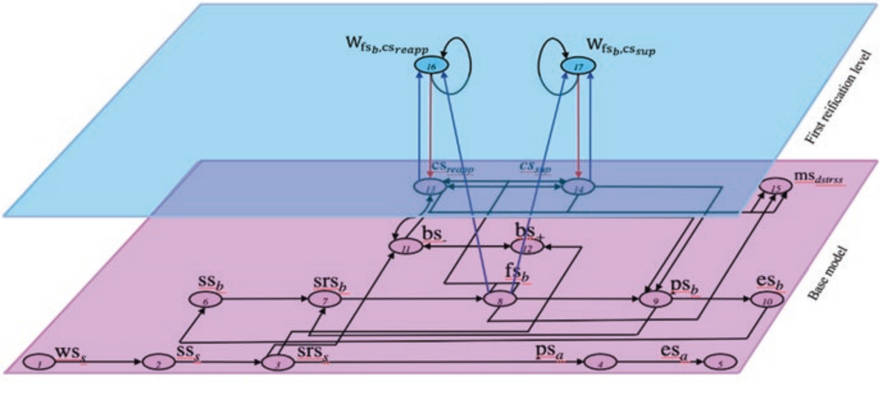


Fig. 11.6 First-order adaptive network model for emotion regulation strategy choice adapting over a longer time

Table 11.3 Overview of the states of the first-order adaptive network model

State		Explanation	Level
X_1	ws_s	World state for stimulus s	Base states
X_2	ss_s	Sensor state for stimulus s	
X_3	srs_s	Sensory representation state for stimulus s	
X_4	ps_a	Preparation state for action a	
X_5	es_a	Execution state for action a	
X_6	ss_b	Sensor state for body state b	
X_7	srs_b	Sensory representation state for body sate b	
X_8	fs_b	Feeling state for body state b	
X_9	ps_b	Preparation state for body state b	
X_{10}	es_b	Expression execution state for body state b	
X_{11}	bs_-	Belief state for negative belief −	
X_{12}	bs_+	Belief state for positive belief +	
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	Control state for reappraisal	
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	Control state for suppression	
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	Monitoring state for distress	
X_{16}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	First-order self-model state for connection weight $\boldsymbol{\omega}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	First-order self-model states
X_{17}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	First-order self-model state for connection weight $\boldsymbol{\omega}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	

connected nodes automatically lead to strengthening of the connection. This form of mental plasticity or adaptation is represented by the self-model states $\mathbf{W}_{X,Y}$ representing the relevant connection weights used at the base level. The Hebbian learning, in this model, is taking place for the (monitoring) connections from fs_b to cs_{reapp} and fs_b to cs_{sup} in the base model, as these are the connections that activate the control states for the regulation strategies, which are assumed to relate to the PFC, and poor emotion regulation is often reported as relating to low activation levels within the PFC. The weights of these connections are represented by self-model states $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{reapp}}$ and $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{sup}}$ respectively.

Note that, in this section, the adaptation itself is not adaptive; e.g., the speed factor of the adaptation (the adaptation rate) is constant. The type of adaptive learning which is based on metaplasticity is addressed in the next section through a second-order adaptive network model.

11.3.2.2 A Simulated Example Scenario Addressing Plasticity in Emotion Regulation

A simulated scenario obtained from the above first-order self-modeling network model is presented in this section. Figure 11.7 displays a number of most relevant base states for the simulated scenario and Fig. 11.8 displays the first-order self-model states, i.e., the **W**-states used for the adaptation.

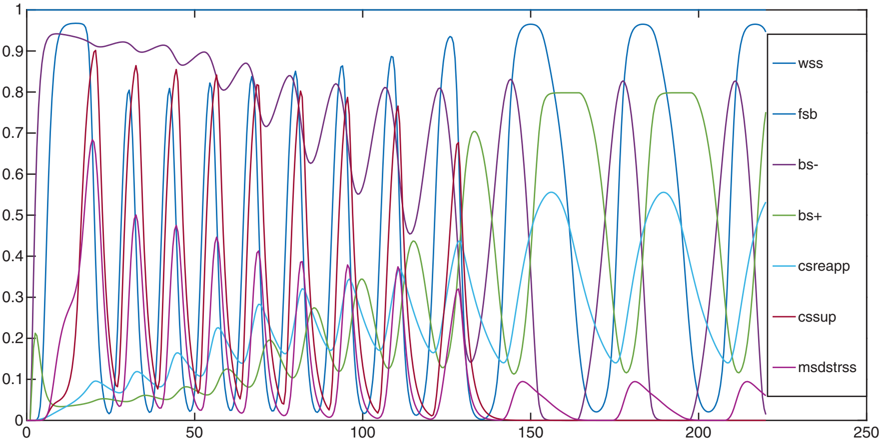


Fig. 11.7 Demonstration of the effective states of the base model over time

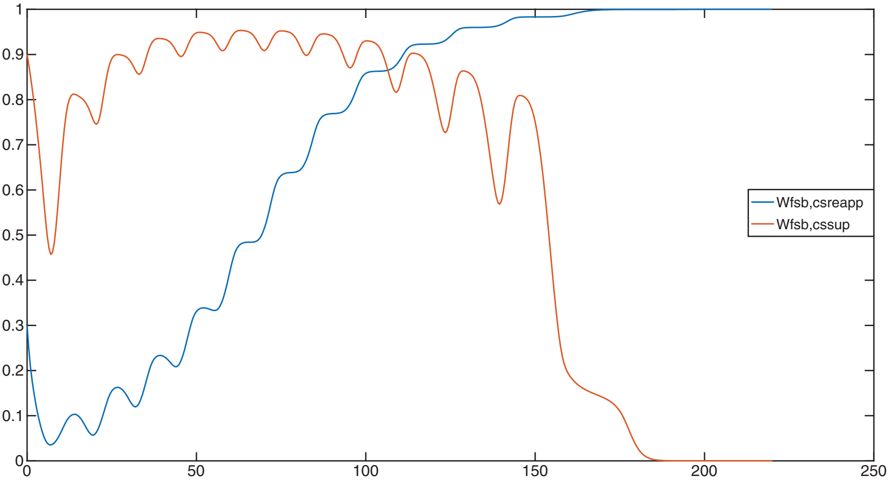


Fig. 11.8 First-order reified representation states over time

In Fig. 11.7 it can be seen that initially the negative belief bs_{-} gets activated which suppresses the positive belief bs_{+}. In the meanwhile, the negative feeling states fs_b also gets higher. The first half of the time scale represents the younger age of a person; therefore, he/she uses suppression. In case of activation of suppression, it can be observed that although the person suppresses the negative feelings, the negative belief bs_{-} still remains high. This reflects how suppression works: nothing changes for the belief. The fluctuation in the simulation results indicate the phenomenon that the regulation only takes place when there is a high level of emotion and as soon the emotion level is getting low, the regulation will stop so that the emotion may get higher again, and so on; this leads to emerging fluctuations. Another issue to be noted here is the monitoring state for distress ms_{dstrss}, which remains high, exactly as found in the literature in case of suppression. But this should decrease in case of reappraisal as per literature.

From the very beginning, it can be observed that the control state for reappraisal cs_{reapp} starts getting higher which represents a gradual shift in the choice of emotion regulation strategies based on underlying mechaisms that generate an emerging pattern over long time periods, so that from a correlational (but not causal) perspective it looks like an increase with age. Control state cs_{reapp} changes the beliefs which means increase in positive belief bs_+ and decrease of negative belief bs_-. This gradual increase finally enables the person to completely switch to reappraisal for the regulation of his emotions. An interesting thing here is the monitoring state for distress ms_{dstrss}, which remains very low exactly as relevant literature suggests in case of reappraisal.

Figure 11.8 gives insight into the states in the first-order self-model: $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{sup}}$ and $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{reapp}}$. In Fig. 11.8, initially $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{sup}}$ is high which represents the use of expressive suppression in the younger age. Over time, $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{reapp}}$ increases slowly and gradually until it reaches 1. It can be seen that as $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{reapp}}$ increases, $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{sup}}$ decreases until it reaches 0. This represents the shift taking place in choice of emotion regulation strategies that emerges over time while age is increasing.

11.4 Higher-Order Adaptation in Emotion Regulation

11.4.1 Metaplasticity in Emotion Regulation

Whether and to what extent plasticity as described above actually takes place is controlled by a form of *metaplasticity*; e.g., (Abraham & Bear, 1996; Garcia, 2002; Magerl et al., 2018; Robinson et al., 2016; Sehgal et al., 2013; Sjöström et al., 2008). For example, according to Robinson and his collogues ((Robinson et al., 2016), p. 2) the following compact quote indicates that due to stimulus exposure, the adaptation speed will increase:

> 'Adaptation accelerates with increasing stimulus exposure'

Similarly, a principle for modulation of persistence of learnt effects can be obtained:

> 'Stimulus exposure modulates persistence of adaptation'

Depending on further context factors, this can be applied in different ways. Reduced persistence can be used in order to be able to get rid of earlier learnt connections that are not effective anymore. However, enhanced persistence can be used to keep what has been learnt. In a similar direction ((Sjöström et al., 2008), p. 773) it is more generally discussed how it depends on the circumstances when the extent of plasticity is or should be high and when it is or should be low in favour of stability:

> 'The Plasticity Versus Stability Conundrum'

All the above are examples of principles describing metaplasticity, which can be considered adaptation of adaptation or second-order adaptation.

Within the cognitive neuroscience literature, Long-Term Potentiation (LTP) is a term used for activity-dependent persistent strengthening of a synapse which plays very important role in long term memory formation and cognitive processing. These patterns produce long lasting increase in signal transmission between two neurons. Opposite of LTP is LTD i.e. long-term depression which causes long lasting decrease in the synaptic strength (Vose & Stanton, 2017). According to (Vose & Stanton, 2017):

> 'Metaplasticity can be thought of as dynamic shifts in the set point for the amount of synaptic activation needed to produce the neurochemical events that induce either LTP or LTD, much like a climate set point determines the mean temperature fluctuations day-to-day.'

This can be seen as a higher-order form of synaptic plasticity. As also illustrated above, it can take place in various forms involving different mechanisms (Abraham & Bear, 1996).

Various examples of metaplasticity in terms of emotions can be found, for instance (Garcia, 2002; Vose & Stanton, 2017). Understanding of this plasticity regulation, has not only provided opportunities for better understanding of some of the mental processes and problems but also opened new vistas for treating those mental problems. According to Garcia (Garcia, 2002), due to high stress levels, a person's cognitive functioning gets poor, and as a result of that the person is no more able to adapt the emotion regulation in order to downregulate his stress: high stress levels slow down or block plasticity. He calls that the negative impact of metaplasticity or negative metaplasticity. Similarly, (Cibrian-Llanderal et al., 2018) also acknowledges the negative role of prolonged stress in cognitive functioning through high level of cortisol in the prefrontal cortex. In contrast, low levels of stress up-regulate this connectivity in the hippocampus which is called positive metaplasticity.

11.4.2 Simulated Scenarios for Metaplasticity in Emotion Regulation

The computational model and simulated scenario presented in this section illustrate the role of metaplasticity in emotion regulation. Again, the above case study will be used for this. First, in Sect. 11.4.2.1 the second-order adaptive computational network used is briefly explained, next, in Sect. 11.4.2.2 a simulated scenario is shown.

11.4.2.1 A Second-Order Adaptive Network Model for Metaplasticity in Emotion Regulation

The second-order adaptive network model used here is an extension of the first-order adaptive network model described in Sect. 11.3.2.1. The current section explains how this model can be extended by adding second-order self-model for the adaptation speed and for the persistence of the adaptation. In the first-order adaptive model, the learning speed and persistence both were constant. In the second-order adaptive network model, the characteristics of the learning are also adaptive, i.e., the speed and persistence characteristic of the learning can change. To achieve this, a second-order self-model is added covering states for these speed and persistence characteristics. The states in the second-order then represent these characteristics of the dynamics of the states in the first-order self-model. For instance, in our case, the newly added second-order self-model states will be responsible for the characteristics of the dynamics of $\mathbf{W}_{\mathrm{fs}_b,'\mathrm{cs}_{sup}}$ and $\mathbf{W}_{\mathrm{fs}_b,'\mathrm{cs}_{reapp}}$. This is achieved by adding a third plane on top of the model displayed in Fig. 11.6 with second-order self-model states such as $\mathbf{H}_{\mathbf{W}_{\mathrm{fs}_b,'\mathrm{cs}_{reapp}}}$ and $\mathbf{M}_{\mathbf{W}_{\mathrm{fs}_b,'\mathrm{cs}_{reapp}}}$, as shown in the upper plane in Fig. 11.9. Within the obtained second-order adaptive model Fig. 11.9, this upper plane represents the concept of metaplasticity where plasticity i.e. learning in our case (as modeled by the middle plane), itself is plastic to changes over time. The nomenclature of the states in the second-order self-model is given in Table 11.4.

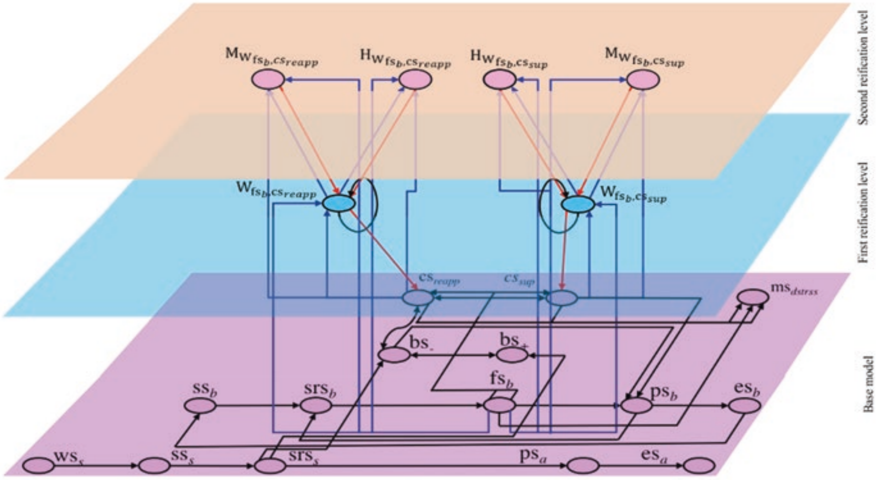


Fig. 11.9 Second-order adaptive network model for emotion regulation strategies over time

Table 11.4 Overview of the states of the second-order self-model

State	Explanation		Level
X_{18}	$\mathbf{M}_{\mathbf{W}_{\mathrm{fs}_b\text{'}\mathrm{cs}_{reapp}}}$	Second-order self-model state for persistence factor $\boldsymbol{\mu}$ for $\mathbf{W}_{\mathrm{fs}_b\text{'}\mathrm{cs}_{reapp}}$	Second-order self-model
X_{19}	$\mathbf{H}_{\mathbf{W}_{\mathrm{fs}_b\text{'}\mathrm{cs}_{reapp}}}$	Second-order self-model state for speed factor $\boldsymbol{\eta}$ for $\mathbf{W}_{\mathrm{fs}_b\text{'}\mathrm{cs}_{reapp}}$	
X_{20}	$\mathbf{H}_{\mathbf{W}_{\mathrm{fs}_b\text{'}\mathrm{cs}_{sup}}}$	Second-order self-model state for speed factor $\boldsymbol{\eta}$ for $\mathbf{W}_{\mathrm{fs}_b\text{'}\mathrm{cs}_{sup}}$	
X_{21}	$\mathbf{M}_{\mathbf{W}_{\mathrm{fs}_b\text{'}\mathrm{cs}_{sup}}}$	Second-order self-model state for persistence factor $\boldsymbol{\mu}$ for $\mathbf{W}_{\mathrm{fs}_b\text{'}\mathrm{cs}_{sup}}$	

Now, as this learning itself can change over time, for instance, increase or decrease, or maybe some of the learned experiences are retained for longer time and some are retained for shorter time. This indeed realizes forms of metaplasticity and is represented in the second-order self-model taking care of second-order adaptation. The speed factor is represented by the **H-**states and the persistence factor is represented by the **M-**states. For instance, the speed and persistence factor adaptation for $\mathbf{W}_{\text{fs}_b, \text{cs}_{reapp}}$ are represented by $\mathbf{H}_{\mathbf{W}_{\text{fs}_b, \text{cs}_{reapp}}}$ and $\mathbf{M}_{\mathbf{W}_{\text{fs}_b, \text{cs}_{reapp}}}$, and $\mathbf{H}_{\mathbf{W}_{\text{fs}_b, \text{cs}_{sup}}}$ and $\mathbf{M}_{\mathbf{W}_{\text{fs}_b, \text{cs}_{sup}}}$, respectively.

An overview of this second-order adaptive network and a full specification is given in Appendixes 2 and 3. This specification is essential for reproducibility of the results shown in this section. For a more detailed study, the concepts can be accessed at (Treur, 2020a, b).

11.4.2.2 A Simulated Example Scenario for Metaplasticity in Emotion Regulation

Inspiration for what is presented in the current section mainly comes from (Gao et al., 2019; Ullah et al., 2020a). The model presented here focuses on shifts for the choice in emotion regulation strategies that emerge over time. Table 11.8 in Appendix 2 provides the initial values of the states of the model.

Figure 11.10 depicts the entire simulated scenario showing all base states involved in the process. This shows a scenario where a person initially uses expressive suppression for his emotion regulation in young age andcognitive reappraisal when older. As mentioned above, the regularity of oscillation in the graphs indicates the fact that the emotion regulation strategies only get activated when the person experiences some negative emotions. Once the emotion levels have been regulated, the strategy gets deactivated. This arousal and regulation of negative emotions and the activation and deactivation of the strategies generate this emerging fluctuation in the graphs. For better analysis of this phenomenon, Fig. 11.11 presents only the key base states involved in this process.

Figures 11.7 and 11.11 display a similar scenario where in the latter there is no metaplasticity: the only difference is that the speed and persistence factors are constant in the latter case while it's adaptive in the former case. When compared to each other, it is clearly visible that in case of adaptive speed factor we have an extra handle to control the speed of the learning/first-order adaptation. This is also closer to the real-world examples.

As above, Figs. 11.8 and 11.12 also display the same states i.e. the **W-**states for the first-order adaptation. The difference here again is that in case of adaptive speed and persistence factors, we can change the characteristics of the first-order adaptation easily and therefore the simulation outcomes are more in our control and realistic.

Figure 11.13 is the representation of the second-order self-model states. These states are $\mathbf{H}_{\mathbf{W}_{\text{fs}_b, \text{cs}_{reapp}}}$, $\mathbf{M}_{\mathbf{W}_{\text{fs}_b, \text{cs}_{reapp}}}$ and $\mathbf{H}_{\mathbf{W}_{\text{fs}_b, \text{cs}_{sup}}}$, $\mathbf{M}_{\mathbf{W}_{\text{fs}_b, \text{cs}_{sup}}}$ which represent the speed

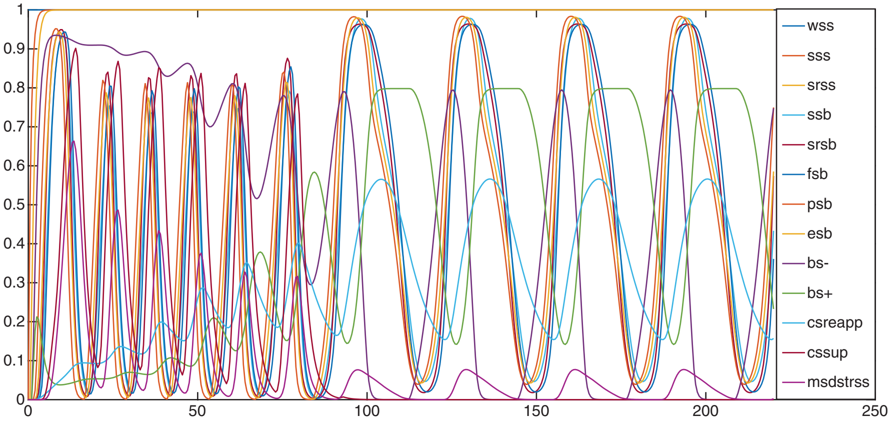


Fig. 11.10 Base states showing switching from Suppression to Reappraisal over time using metaplasticity

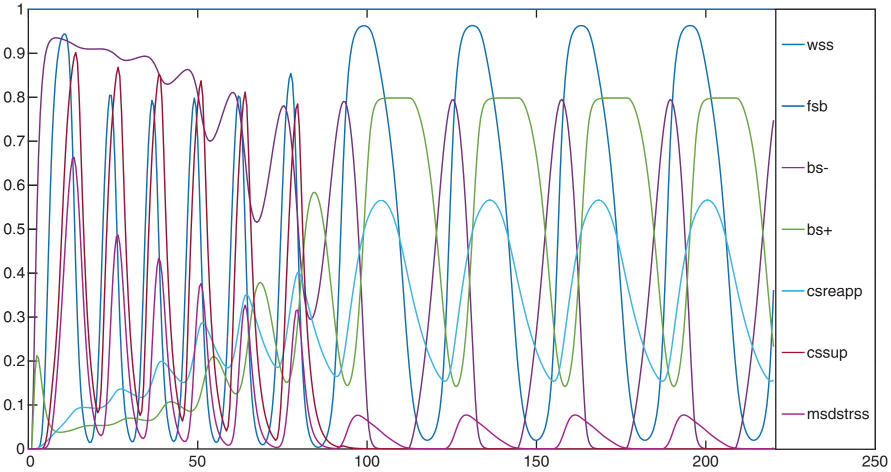


Fig. 11.11 The effective base states over time using metaplasticity

and the persistence factors of $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{reapp}}$ and $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{sup}}$, respectively. It can be observed that initially the speed and persistence factors of $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{sup}}$ are quite high but this starts decreasing and hits zero once the speed and persistence factor of $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{reapp}}$ reaches 1. This happens because of the shift that's taking place from suppression to reappraisal as a person grows. This phenomenon represents metaplasticity as defined in the relevant literature.

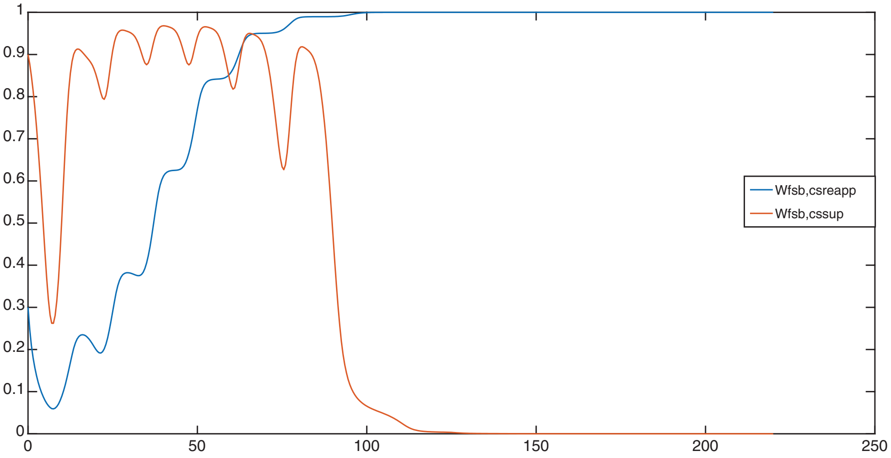


Fig. 11.12 First-order self-model states over time using metaplasticity

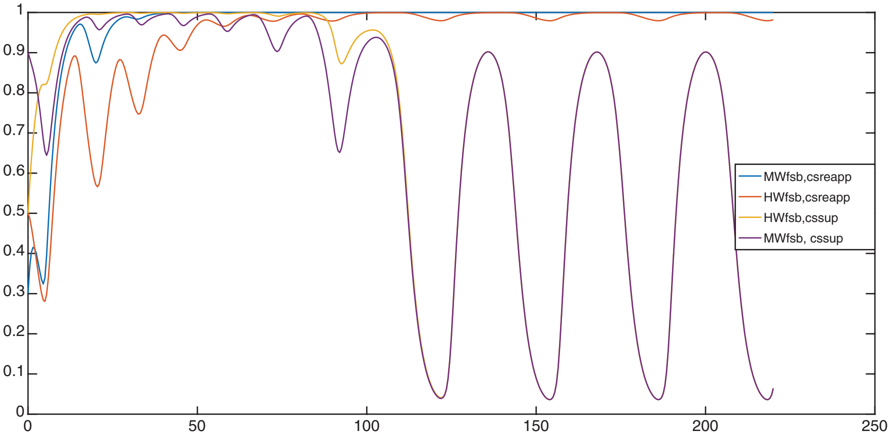


Fig. 11.13 Second-order self-model states for adaptation speed and persistence factors

11.5 Summary

In this chapter, the focus was on the computational analysis of emotion regulation specifically concerning flexibility and adaptivity. The concept of flexibility in emotion regulation strategies has recently gained momentum, with various studies yielding findings that support this notion. It is clear that specific strategies are not inherently adaptive or maladaptive, given that research has found that each strategy has the capacity to outclass other strategies in various situations. An important question is which strategy is used for which situation.

The answer to this question may lie in a broader repertoire with capabilities of decision making and analysis. A person with a broader repertoire of strategies has edge over a person using just a few strategies irrespective of the situation. For this purpose, the right decisions need to be taken for which strategy to use. This continuous adaptation of regulation and decision making also enables the person to know which strategy to use in which situation over longer period of time. This process of plasticity is taking place from very early life. In addition, plasticity of plasticity, also called metaplasticity, occurs, which adds control to the adaptation process.

These highly dynamic concepts have been modeled using a network-oriented modeling approach based on self-modeling temporal-causal networks (Treur, 2020a). This approach can easily be used for modeling any temporal phenomenon, such as the dynamics of emotions, desires and any other mental states. Moreover, the concepts of plasticity and metaplasticity can very easily and efficiently be modeled by using this approach. Apart from giving deep insight into complex phenomenon through the simulation results, this approach can model a very wide variety of complex problems.

The models presented in this chapter focus on the choice for using a certain emotion regulation strategy depending on specific circumstances, in line with studies like (Sheppes, 2014; Sheppes et al., 2011) where flexibility in emotion regulation strategies is the main concern. However, besides the question which strategy to use in which situation, in many cases, simply choosing an emotion regulation strategy is not enough to ensure its implementation. A chosen strategy can run into difficulties. Therefore, as a next challenge for future research, we aim to consider recent findings on maintaining a strategy, for instance, as addressed in (Gallo et al., 2009; Webb et al., 2012b). This has further been explored in (Pruessner et al., 2020) wherein selection and maintenance of a strategy has been differentiated. This means that a strategy, once chosen, has to be shielded against interference from other strategies and difficulties.

11.6 Further Reading

A preliminary version of part of this work was published in (Ullah & Treur, 2020b; Ullah et al., 2020b). Moreover, for more study about computational modeling of emotion regulation see, (Ullah & Treur, 2020c, d). For further literature on flexibility in emotion regulation, see, for example, (Cheng, 2001; Cheng et al., 2014; Troy et al., 2013). Also literature such as this can provide inspiration for further development of computational models for emotion regulation by addressing other factors that for the sake of simplicity have been left out of consideration in this chapter.

Appendix 1: Network-Oriented Modeling

Network-Oriented Modeling Based on Temporal-Causal Networks

All the modeling concepts used in this chapter are based on Network-Oriented Modeling by self-modeling temporal-causal networks (Treur, 2020a), see also (Treur, 2016). An overview of the basis for this modeling approach are the network characteristics for connectivity, aggregation and timing presented in Table 11.1. A phenomenon is represented in a network form which consists of nodes with activation levels that vary over time. Each node Y, also called state, has incoming connections from some other states X through connections with weights, which defines the causal impact of such a state X on state Y over time. A temporal-network model can be represented as a labelled graph for its network characteristics in which:

- **Connectivity characteristics**
- Each connection carries some *connection weight* from one state to another called *impact* represent by $\boldsymbol{\omega}_{X,Y.}$

- **Aggregation characteristics**
- There's some way to *aggregate multiple impacts* $\boldsymbol{\omega}_{X,Y}X(t)$ from some states X on a state Y by a combination function $\mathbf{c}_Y(..)$.

- **Timing characteristics**
- There's a notion of *speed of change* of each state to define how faster a state changes because of the incoming impact (speed factor $\boldsymbol{\eta}_Y$).

A temporal-causal network is fully defined by these three types of characteristics, which in a canonical manner define the numerical representation of the model; see Table 11.1 for more explanation of the terms and for these numerical representations. A dedicated software environment takes as input the above network characteristics and automatically (and hidden for the modeler) generates a numerical representation as described in the lower part of Table 11.5.

This approach provides a library of currently 40 combination functions for the aggregation of multiple (incoming) causal impacts. Apart from the available combination functions, an option is provided to easily create any function compositions of any of the available functions, and if that is still not enough, any own-defined functions can also be added to the library. This makes the technique even more flexible and user friendly. All software components, including the library, can be freely downloaded from URL https://www.researchgate.net/project/Network-Oriented-Modeling-Software.

Table 11.5 Basics of a temporal-causal network model

Concept	Conceptual representation	Explanation
States and connections	X, Y, $X \rightarrow Y$	Describes the nodes and links of a network structure (e.g., in graphical or matrix form)
Connection weight	$\boldsymbol{\omega}_{X,Y}$	The *connection weight* $\boldsymbol{\omega}_{X,Y}$ usually in [−1, 1] represents the strength of the causal impact of state X on state Y through connection $X \rightarrow Y$
Aggregating multiple impacts on a state	$\mathbf{c}_Y(..)$	For each state Y a *combination function* $\mathbf{c}_Y(..)$ is chosen to combine the causal impacts of other states on state Y
Timing of the effect of causal impact	$\boldsymbol{\eta}_Y$	For each state Y a *speed factor* $\boldsymbol{\eta}_Y \geq 0$ is used to represent how fast a state is changing upon causal impact
Concept	**Numerical representation**	**Explanation**
State values over time t	$Y(t)$	At each time point t each state Y in the model has a real number value, usually in [0, 1]
Single causal impact	$\mathbf{impact}_{X,Y}(t) = \boldsymbol{\omega}_{X,Y}\, X(t)$	At t state X with a connection to state Y has impact on Y, using connection weight $\boldsymbol{\omega}_{X,Y}$
Aggregating multiple causal impacts	$\mathbf{aggimpact}_Y(t) = \mathbf{c}_Y(\mathbf{impact}_{X_1,Y}(t), \ldots, \mathbf{impact}_{X_k,Y}(t)) = \mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y} X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y} X_k(t))$	The aggregated causal impact of multiple states X_i on Y at t, is determind using combination function $\mathbf{c}_Y(..)$
Timing of the causal effect	$Y(t + \Delta t) = Y(t) + \boldsymbol{\eta}_Y [\mathbf{aggimpact}_Y(t) - Y(t)]\, \Delta t = Y(t) + \boldsymbol{\eta}_Y [\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y} X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y} X_k(t)) - Y(t)]\, \Delta t$	The causal impact on Y is exerted over time gradually, using speed factor $\boldsymbol{\eta}_Y$; here the X_i are all states with outgoing connections to state Y

Note that the numerical representation in the lower part of Table 11.1 fully describes the dynamics of the temporal-causal network in terms of the network structure characteristics. This formal numerical representation associates detailed mathematically defined semantics to any temporal-causal network and also allows to mathematically analyze how emergent network behaviour depends on network structure, as has been done in (Treur, 2020a), Chaps. 11–14.

Self-Models Representing Network Characteristics by Network States

As indicated above, ‘network characteristics’ and ‘network states’ are two distinct concepts for a network. Self-modeling or reification as described in detail in (Treur, 2020a) is a way to relate these distinct concepts to each other in an interesting and useful way. A *self-model* is making the implicit network characteristics (such as connection weights) explicit in the form of adding states for these characteristics and connections for these states; thus, the network gets an internal self-model of part of the network structure itself. In this way, by iteration different self-modeling levels can be created where network characteristics from one level relate to explicit states at a next level. Thus, an arbitrary number of self-modeling levels can be modeled, covering *second-order* or *higher-order* effects. More specifically, adding a self-model for a temporal-causal base network is done in the way that for some of the states Y of the base network and some of the network structure characteristics for connectivity, aggregation and timing (i.e., some from $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{j,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$), additional network states $\mathbf{W}_{X,Y}$, $\mathbf{C}_{j,Y}$, $\mathbf{P}_{i,j,Y}$, $\mathbf{H}_Y$ (called *self-model states* or *reification states*) are introduced and connected to other states:

(a) **Connectivity self-model**

- Self-model states $\mathbf{W}_{X,Y}$ are added representing connectivity characteristics, in particular connection weights $\boldsymbol{\omega}_{X,Y}$

(b) **Aggregation self-model**

- Self-model states $\mathbf{C}_{j,Y}$ are added representing aggregation characteristics, in particular combination function weights $\boldsymbol{\gamma}_{j,Y}$
- Self-model states $\mathbf{P}_{i,j,Y}$ are added representing aggregation characteristics, in particular combination function parameters $\boldsymbol{\pi}_{i,j,Y}$

(c) **Timing self-model**

- Self-model states $\mathbf{H}_Y$ are added representing timing characteristics, in particular speed factors $\boldsymbol{\eta}_Y$

The notations $\mathbf{W}_{X,Y}$, $\mathbf{C}_{j,Y}$, $\mathbf{P}_{i,j,Y}$, $\mathbf{H}_Y$ for the self-model states indicate the referencing relation with respect to the characteristics $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{j,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$: here $\mathbf{W}$ refers to $\boldsymbol{\omega}$, $\mathbf{C}$ refers to $\boldsymbol{\gamma}$, $\mathbf{P}$ refers to $\boldsymbol{\pi}$, and $\mathbf{H}$ refers to $\boldsymbol{\eta}$, respectively. For the processing, these self-model states define the dynamics of any state Y in a canonical manner according to the equations in the bottom row of Table 11.5 whereby the values of $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{j,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$ are replaced by the state values of $\mathbf{W}_{X,Y}$, $\mathbf{C}_{j,Y}$, $\mathbf{P}_{i,j,Y}$, $\mathbf{H}_Y$ at time t, respectively. To model certain adaptation principles by a self-modeling network, the dynamics of each self-model state itself and it effect on another state are specified for one of the three general types of network structure characteristics *connectivity* (a), *aggregation* (b), and *timing* (c), also mentioned above:

(a) **Connectivity for the self-model states in a self-modeling network**

For the self-model states their *connectivity* in terms of their incoming and outgoing connections has two different functions:

- **Effectuating its special effect from its specific role**

- The *outgoing downward causal connections* from the self-model states $\mathbf{W}_{X,Y}$, $\mathbf{C}_{j,Y}$, $\mathbf{P}_{i,j,Y}$, $\mathbf{H}_Y$ to state Y represent the specific causal impact (its *special effect* from its specific *role*) each of these self-model states has on Y. These downward causal impacts are standard per role, and make that the adaptive values $\mathbf{W}_{X,Y}(t)$, $\mathbf{C}_{j,Y}(t)$, $\mathbf{P}_{i,j,Y}(t)$, $\mathbf{H}_Y(t)$ are used for the adaptive characteristics of the base network in (9).

- **Indicating the input for the adaptation principle as specified in (b)**

- The *incoming upward or leveled connections* to a self-model state are used to specify the *input* needed for *the particular adaptation principle* that is addressed.

(b) **Aggregation for the self-model states in a self-modeling network**

For the self-model states their aggregation characteristics have one main aim:

- **Expressing the aggregation adaptation principle by a mathematical function**

- For the *aggregation* of the incoming causal impacts for a self-model state, provided as indicated in (a), a specific combination function is chosen *to express the adaptation principle* in a declarative mathematical manner.

(c) **Timing for the self-model states in a self-modeling network**

For the self-model states their timing characteristics have one main aim:

- **Expressing the timing adaptation principle by a number**

- Finally, like any other state self-model states have their own *timing* in terms of speed factors. These speed factors are used as the *means to express the adaptation speed*.

An example of an aggregation self-model state $\mathbf{P}_{i,j,Y}$ for a combination function parameter $\boldsymbol{\pi}_{i,j,Y}$ is for the excitability threshold $\boldsymbol{\tau}_Y$ of state Y, which is the second parameter of a logistic sum combination function; then $\mathbf{P}_{i,j,Y}$ is usually indicated by $\mathbf{T}_Y$, where $\mathbf{T}$ refers to $\boldsymbol{\tau}$. The network constructed by the addition of a self-model to a base network is called a *self-modeling network* or a *reified network* for this base network. This constructed network is also a temporal-causal network model itself, as has been shown in (Treur, 2020a), Ch 10; for this reason, this construction can easily be applied iteratively to obtain multiple levels or orders of self-models, in which case the resulting network is called a *multi-level* or *multi-order* or *higher-order self-modeling network* or *reified network*.

Appendix 2: Tables

In Table 11.6 a state can either have value of scaling factor (λ) for which scale sum function has been used or it can have values for steepness (σ) and threshold (τ) for which alogistic combination function has been used.

Table 11.6 Values used for alogistic, scaled-sum combination functions and speed factor

state	λ	τ	σ	η	state	τ	σ	η
ws_s	0.94	0	0	0.1	ms_2	0.5	50	0.5
ss_s	0	0	0	0.5	$\mathrm{bs}_{(-)c.p}$	0.1	50	0.5
ss_b	0	0	0	0.5	$\mathrm{bs}_{(+)c.p}$	0.5	17	0.5
srs_s	1	0	0	0.5	cs_{reapp}	0.5	8	0.15
srs_b	1.4	0	0	0.5	$\mathrm{cs}_{a.d}$	0.85	12	0.2
bs_-	0.91	0	0	0.5	$\mathrm{cs}_{s.m}$	0.85	12	0.3
bs_+	0	0.1	10	0.5	cs_{sup}	0.5	6	0.15
ps_b	1.8	0	0	0.5	ps_a	0.6	5	0.5
es_b	0.98	0	0	0.5	$\mathrm{ps}_{a.d}$	0	0	0.3
fs_b	1	0	0	0.5	es_a	0.5	3	0.5
ms_1	0	0.1	5	0.5	$\mathrm{es}_{a.d}$	0	0	0.3

Table 11.7 Values used for connection weights

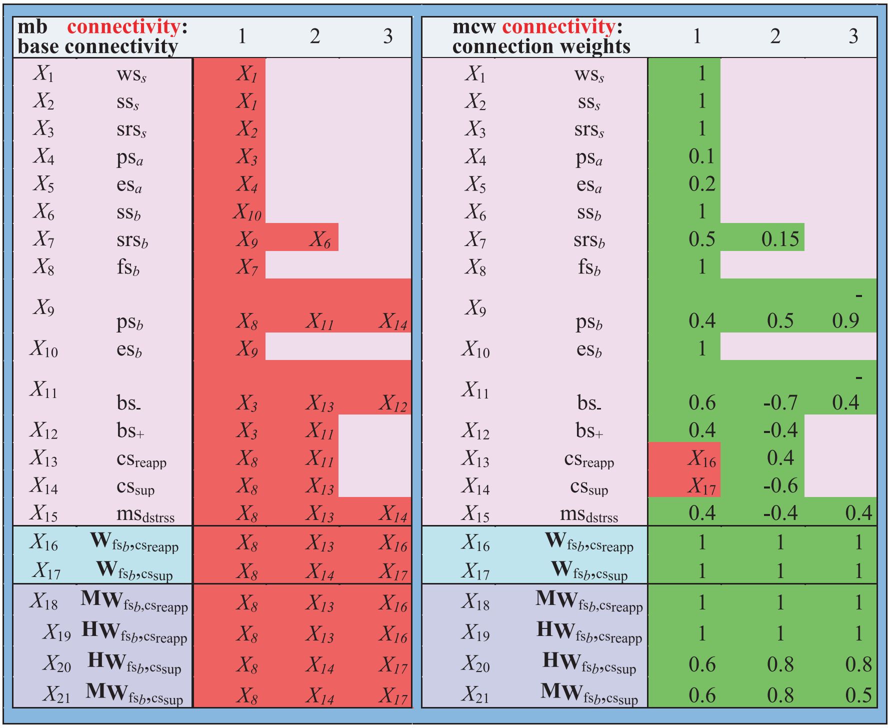
Connection	Weight	Connection	Weight	Connection	Weight	Connection	Weight
$\omega_{\mathrm{ws}s,\ \mathrm{ws}s}$	0.95	$\omega_{\mathrm{bs+},\ \mathrm{bs-}}$	−0.4	$\omega_{\mathrm{cs}reapp,\ \mathrm{cs}s.m}$	−1	$\omega_{\mathrm{fs}b,\ \mathrm{ms}1}$	0.5
$\omega_{\mathrm{ws}s,\ \mathrm{ss}s}$	1	$\omega_{\mathrm{ms}1,\ \mathrm{cs}reapp}$	0.2	$\omega_{\mathrm{cs}reapp,\ \mathrm{cs}sup}$	−1	$\omega_{\mathrm{fs}b,\ \mathrm{ms2}}$	0.8
$\omega_{\mathrm{ss}s,\ \mathrm{srs}s}$	1	$\omega_{\mathrm{ms}1,\ \mathrm{cs}sup}$	0.4	$\omega_{\mathrm{cs}a.d,\ \mathrm{ps}a.d}$	1	$\omega_{\mathrm{fsb},\ \mathrm{bs}(-)c.p}$	0.5
$\omega_{\mathrm{ss}b,\ \mathrm{srs}b}$	0.7	$\omega_{\mathrm{ms2},\ \mathrm{ms}1}$	−1	$\omega_{\mathrm{cs}a.d,\ \mathrm{cs}s.m}$	−1	$\omega_{\mathrm{fsb},\ \mathrm{bs}(+)c.p}$	0.5
$\omega_{\mathrm{srs}s,\ \mathrm{bsc-}}$	0.9	$\omega_{\mathrm{ms2},\ \mathrm{cs}a.d}$	0.35	$\omega_{\mathrm{cs}a.d,\ \mathrm{cs}sup}$	−1	$\omega_{\mathrm{fs}b,\ \mathrm{ps}b}$	0.9
$\omega_{\mathrm{srs}s,\ \mathrm{bsc+}}$	0.4	$\omega_{\mathrm{ms2},\ \mathrm{cs}s.m}$	0.5	$\omega_{\mathrm{cs}s.m,\ \mathrm{ps}a}$	0.8	$\omega_{\mathrm{ps}a,\ \mathrm{es}a}$	0.5
$\omega_{\mathrm{srs}s,\ \mathrm{ps}a}$	0.3	$\omega_{\mathrm{bs}(-)c.p,\ \mathrm{bs}(+)c.p}$	−1	$\omega_{\mathrm{cs}s.m,\ \mathrm{es}a}$	0.8	$\omega_{\mathrm{ps}b,\ \mathrm{srs}b}$	0.75
$\omega_{\mathrm{srs}c.p,\ \mathrm{bs}(-)c.p}$	−1	$\omega_{\mathrm{bs}(-)c.p,\ \mathrm{cs}sup}$	0.3	$\omega_{\mathrm{cs}s.m,\ \mathrm{cs}reapp}$	−1	$\omega_{\mathrm{ps}b,\ \mathrm{es}b}$	1
$\omega_{\mathrm{srs}c.p,\ \mathrm{bs}(+)c.p}$	1	$\omega_{\mathrm{bs}(-)c.p,\ \mathrm{cs}a.d}$	0.6	$\omega_{\mathrm{cs}s.m,\ \mathrm{cs}a.d}$	−1	$\omega_{\mathrm{ps}a.d,\ \mathrm{es}a.d}$	1
$\omega_{\mathrm{srs}b,\ \mathrm{fs}b}$	1	$\omega_{\mathrm{bs}(+)c.p,\ \mathrm{bs}(-)c.p}$	−1	$\omega_{\mathrm{cs}sup,\ \mathrm{ps}b}$	−1	$\omega_{\mathrm{es}a,\ \mathrm{ws}s}$	−0.5
$\omega_{\mathrm{bs-},\ \mathrm{bs+}}$	−0.4	$\omega_{\mathrm{bs}(+)c.p,\ \mathrm{cs}s.m}$	0.5	$\omega_{\mathrm{cs}sup,\ esb}$	−0.2	$\omega_{\mathrm{es}b,\ \mathrm{ss}b}$	1
$\omega_{\mathrm{bs-},\ \mathrm{cs}reapp}$	0.05	$\omega_{\mathrm{bs}(+)c.p,\ \mathrm{cs}reapp}$	0.33	$\omega_{\mathrm{cs}sup,\ \mathrm{cs}reapp}$	−1	$\omega_{\mathrm{es}a.d,\ \mathrm{srs}s}$	0.63
$\omega_{\mathrm{bs-},\ \mathrm{ps}b}$	1	$\omega_{\mathrm{cs}reapp,\ \mathrm{bs-}}$	−0.35	$\omega_{\mathrm{cs}sup,\ \mathrm{cs}a.d}$	−1		

Table 11.8 Initial values of the states

State	ws_s	All other base states	$\mathbf{W}_{\mathrm{fs}_b\,'\mathrm{cs}_{reapp}}$	$\mathbf{W}_{\mathrm{fs}_b\,'\mathrm{cs}_{sup}}$	$\mathbf{H}_{\mathbf{W}_{\mathrm{fs}_b\,'\mathrm{cs}_{reapp}}}$	$\mathbf{H}_{\mathbf{W}_{\mathrm{fs}_b\,'\mathrm{cs}_{sup}}}$	$\mathbf{M}_{\mathbf{W}_{\mathrm{fs}_b\,'\mathrm{cs}_{reapp}}}$	$\mathbf{M}_{\mathbf{W}_{\mathrm{fs}_b\,'\mathrm{cs}_{sup}}}$
Initial value	1	0	0.3	0.9	0.5	0.5	0.9	0.9

11.7 Appendix 3: Role Matrices

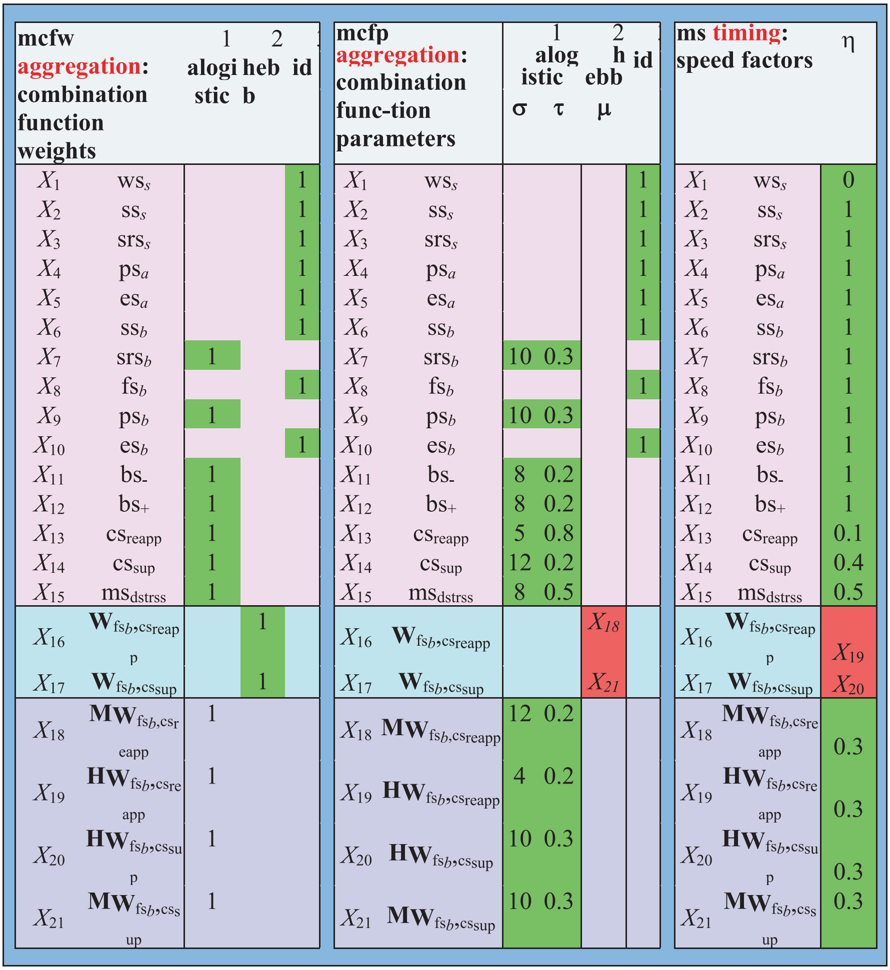
The red cells with $\boldsymbol{X}_{\mathbf{i}}$ in them represent the adaptive dynamics of that connections in matrices **mcw,mcfp** and **ms**. For instance, $\boldsymbol{X}_{\mathbf{16}}$ in the red cell in **mcw** refers to $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{reapp}}$ and this state represent the adaptivity taking place at connection from $\mathrm{fs}_{\boldsymbol{b}}$ to $\mathrm{cs}_{\boldsymbol{reapp}}$. Similarly, the $\boldsymbol{X}_{\mathbf{18}}$ and $\boldsymbol{X}_{\mathbf{19}}$ in mcfp and ms represents the persistence and speed factor of $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{reapp}}$, respectively (Figs. 11.14 and 11.15).



mb **connectivity:** **base connectivity**		1	2	3
X_1	ws_s	X_1		
X_2	ss_s	X_1		
X_3	srs_s	X_2		
X_4	ps_a	X_3		
X_5	es_a	X_4		
X_6	ss_b	X_{10}		
X_7	srs_b	X_9	X_6	
X_8	fs_b	X_7		
X_9	ps_b	X_8	X_{11}	X_{14}
X_{10}	es_b	X_9		
X_{11}	bs_-	X_3	X_{13}	X_{12}
X_{12}	bs_+	X_3	X_{11}	
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	X_8	X_{11}	
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	X_8	X_{13}	
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	X_8	X_{13}	X_{14}
X_{16}	$\mathbf{W}_{\mathrm{fs}b,\mathrm{cs}\mathrm{reapp}}$	X_8	X_{13}	X_{16}
X_{17}	$\mathbf{W}_{\mathrm{fs}b,\mathrm{cs}\mathrm{sup}}$	X_8	X_{14}	X_{17}
X_{18}	$\mathbf{MW}_{\mathrm{fs}b,\mathrm{cs}\mathrm{reapp}}$	X_8	X_{13}	X_{16}
X_{19}	$\mathbf{HW}_{\mathrm{fs}b,\mathrm{cs}\mathrm{reapp}}$	X_8	X_{13}	X_{16}
X_{20}	$\mathbf{HW}_{\mathrm{fs}b,\mathrm{cs}\mathrm{sup}}$	X_8	X_{14}	X_{17}
X_{21}	$\mathbf{MW}_{\mathrm{fs}b,\mathrm{cs}\mathrm{sup}}$	X_8	X_{14}	X_{17}

mcw **connectivity:** **connection weights**		1	2	3
X_1	ws_s	1		
X_2	ss_s	1		
X_3	srs_s	1		
X_4	ps_a	0.1		
X_5	es_a	0.2		
X_6	ss_b	1		
X_7	srs_b	0.5	0.15	
X_8	fs_b	1		
X_9	ps_b	0.4	0.5	-0.9
X_{10}	es_b	1		
X_{11}	bs_-	0.6	-0.7	-0.4
X_{12}	bs_+	0.4	-0.4	
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	X_{16}	0.4	
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	X_{17}	-0.6	
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	0.4	-0.4	0.4
X_{16}	$\mathbf{W}_{\mathrm{fs}b,\mathrm{cs}\mathrm{reapp}}$	1	1	1
X_{17}	$\mathbf{W}_{\mathrm{fs}b,\mathrm{cs}\mathrm{sup}}$	1	1	1
X_{18}	$\mathbf{MW}_{\mathrm{fs}b,\mathrm{cs}\mathrm{reapp}}$	1	1	1
X_{19}	$\mathbf{HW}_{\mathrm{fs}b,\mathrm{cs}\mathrm{reapp}}$	1	1	1
X_{20}	$\mathbf{HW}_{\mathrm{fs}b,\mathrm{cs}\mathrm{sup}}$	0.6	0.8	0.8
X_{21}	$\mathbf{MW}_{\mathrm{fs}b,\mathrm{cs}\mathrm{sup}}$	0.6	0.8	0.5

Box 1 Role matrices for connectivity



mcfw **aggregation**: **combination function weights**		1 **alogistic**	2 **hebb**	**id**
X_1	ws_s			1
X_2	ss_s			1
X_3	srs_s			1
X_4	ps_a			1
X_5	es_a			1
X_6	ss_b			1
X_7	srs_b	1		
X_8	fs_b			1
X_9	ps_b	1		
X_{10}	es_b			1
X_{11}	bs_-	1		
X_{12}	bs_+	1		
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	1		
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	1		
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	1		
X_{16}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$		1	
X_{17}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$		1	
X_{18}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	1		
X_{19}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	1		
X_{20}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	1		
X_{21}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	1		

mcfp **aggregation**: **combination func-tion parameters**		1 **alogistic** σ	τ	2 **hebb** μ	**id**
X_1	ws_s				1
X_2	ss_s				1
X_3	srs_s				1
X_4	ps_a				1
X_5	es_a				1
X_6	ss_b				1
X_7	srs_b	10	0.3		
X_8	fs_b				1
X_9	ps_b	10	0.3		
X_{10}	es_b				1
X_{11}	bs_-	8	0.2		
X_{12}	bs_+	8	0.2		
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	5	0.8		
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	12	0.2		
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	8	0.5		
X_{16}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$			X_{18}	
X_{17}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$			X_{21}	
X_{18}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	12	0.2		
X_{19}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	4	0.2		
X_{20}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	10	0.3		
X_{21}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	10	0.3		

ms **timing**: **speed factors**		η
X_1	ws_s	0
X_2	ss_s	1
X_3	srs_s	1
X_4	ps_a	1
X_5	es_a	1
X_6	ss_b	1
X_7	srs_b	1
X_8	fs_b	1
X_9	ps_b	1
X_{10}	es_b	1
X_{11}	bs_-	1
X_{12}	bs_+	1
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	0.1
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	0.4
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	0.5
X_{16}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	X_{19}
X_{17}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	X_{20}
X_{18}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	0.3
X_{19}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	0.3
X_{20}	$\mathbf{HW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	0.3
X_{21}	$\mathbf{MW}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	0.3

Box 2 Role matrices for aggregation and timing

References

Abraham, W. C. (2008). Metaplasticity: Tuning synapses and networks for plasticity. *Nature Reviews Neuroscience, 9*(5), 387–399. https://doi.org/10.1038/nrn2356

Abraham, W. C., & Bear, M. F. (1996). Metaplasticity: The plasticity of synaptic plasticity. *Trends in Neurosciences, 19*(4), 126–130. https://doi.org/10.1016/S0166-2236(96)80018-X

Aldao, A. (2013). The future of emotion regulation research. *Perspectives on Psychological Science, 8*(2), 155–172. https://doi.org/10.1177/1745691612459518

Aldao, A., & Nolen-Hoeksema, S. (2012). The influence of context on the implementation of adaptive emotion regulation strategies. *Behaviour Research and Therapy, 50*(7–8), 493–501. https://doi.org/10.1016/j.brat.2012.04.004

Aldao, A., Sheppes, G., & Gross, J. J. (2015). Emotion regulation flexibility. *Cognitive Therapy and Research, 39*(3), 263–278. https://doi.org/10.1007/s10608-014-9662-4

Bechara, A., Damasio, H., & Damasio, A. R. (2003). Role of the amygdala in decision-making. *Annals of the New York Academy of Sciences, 985*, 356–369. https://doi.org/10.1111/j.1749-6632.2003.tb07094.x

Bonanno, G. A., & Burton, C. L. (2013a). Regulatory flexibility: An individual differences perspective on coping and emotion regulation. *Perspectives on Psychological Science, 8*(6), 591–612. https://doi.org/10.1177/1745691613504116

Bonanno, G. A., & Burton, C. L. (2013b). Regulatory flexibility. *Perspectives on Psychological Science, 8*(6), 591–612. https://doi.org/10.1177/1745691613504116

Brandtstädter, J., & Renner, G. (1990). Tenacious goal pursuit and flexible goal adjustment: Explication and age-related analysis of assimilative and accommodative strategies of coping. *Psychology and Aging, 5*(1), 58–67. https://doi.org/10.1037/0882-7974.5.1.58

Carstensen, L. L., Isaacowitz, D. M., & Charles, S. T. (1999). Taking time seriously: A theory of socioemotional selectivity. *American Psychologist, 54*(3), 165–181. https://doi.org/10.1037/0003-066X.54.3.165

Carstensen, L. L., Pasupathi, M., Mayr, U., & Nesselroade, J. R. (2000). Emotional experience in everyday life across the adult life span. *Journal of Personality and Social Psychology, 79*(4), 644–655.

Charles, S. T. (2010). Strength and vulnerability integration: A model of emotional well-being across adulthood. *Psychological Bulletin, 136*(6), 1068–1091. https://doi.org/10.1037/a0021232

Charles, S. T., & Carstensen, L. L. (2007). Emotion regulation and aging. In *Handbook of emotion regulation* (pp. 307–327). The Guilford Press.

Cheng, C. (2001). Assessing coping flexibility in real-life and laboratory settings: A multimethod approach. *Journal of Personality and Social Psychology, 80*(5), 814–833.

Cheng, C., Lau, H. P. B., & Chan, M. P. S. (2014). Coping flexibility and psychological adjustment to stressful life changes: A meta-analytic review. *Psychological Bulletin, 140*(6), 1582.

Cibrian-Llanderal, T., Melgarejo-Gutierrez, M., & Hernandez-Baltazar, D. (2018). Stress and cognition: Psychological basis and support resources. In *Health and academic achievement* (p. 13). InTech.

Cutuli, D. (2014). Cognitive reappraisal and expressive suppression strategies role in the emotion regulation: An overview on their modulatory effects and neural correlates. *Frontiers in Systems Neuroscience, 8*(175), 1–6. https://doi.org/10.3389/fnsys.2014.00175

Dworkin, J. D., Zimmerman, V., Waldinger, R. J., & Schulz, M. S. (2019). Capturing naturally occurring emotional suppression as it unfolds in couple interactions. *Emotion, 19*(7), 1224–1235. https://doi.org/10.1037/emo0000524

Folkman, S., Lazarus, R. S., Pimley, S., & Novacek, J. (1987). Age differences in stress and coping processes. *Psychology and Aging, 2*(2), 171–184. https://doi.org/10.1037/0882-7974.2.2.171

Ford, B. Q., & Troy, A. S. (2019). Reappraisal reconsidered: A closer look at the costs of an acclaimed emotion-regulation strategy. *Current Directions in Psychological Science, 28*(2), 195–203. https://doi.org/10.1177/0963721419827526

Gallo, I. S., Keil, A., McCulloch, K. C., Rockstroh, B., & Gollwitzer, P. M. (2009). Strategic automation of emotion regulation. *Journal of Personality and Social Psychology, 96*(1), 11–31. https://doi.org/10.1037/a0013460

Gao, Z., Liu, R., & Ullah, N. (2019). A temporal-causal network model for age and gender difference in choice of emotion regulation strategies. In N. T. Nguyen, R. Chbeir, E. Exposito, P. Aniorté, & B. Trawiński (Eds.), *International Confernce on Computational Collective Intelligence. ICCCI 2019. Lecture Notes in Computer Science* (pp. 106–117). Springer International Publishing.

Garcia, R. (2002). Stress, metaplasticity, and antidepressants. *Current Molecular Medicine, 2*(7), 629–638. https://doi.org/10.2174/1566524023362023

Giuliani, N. R., Drabant, E. M., Bhatnagar, R., & Gross, J. J. (2011). Emotion regulation and brain plasticity: Expressive suppression use predicts anterior insula volume. *NeuroImage, 58*(1), 10–15. https://doi.org/10.1016/j.neuroimage.2011.06.028

Gross, J. J. (1998). The emerging field of emotion regulation: An integrative review. *Review of General Psychology, 2*(3), 271–299. https://doi.org/10.1037/1089-2680.2.3.271

Gross, J. J. (2001). Emotion regulation in adulthood: Timing is everything. *Current Directions in Psychological Science, 10*(6), 214–219. https://doi.org/10.1111/1467-8721.00152

Gross, J. J. (2015). The extended process model of emotion regulation: Elaborations, applications, and future directions. *Psychological Inquiry, 26*(1), 130–137. https://doi.org/10.1080/1047840X.2015.989751

Gross, J. J., Carstensen, L. L., Pasupathi, M., Tsai, J., Götestam Skorpen, C., & Hsu, A. Y. C. (1997). Emotion and aging: Experience, expression, and control. *Psychology and Aging, 12*(4), 590–599. https://doi.org/10.1037/0882-7974.12.4.590

Haga, S. M., Kraft, P., & Corby, E.-K. (2009). Emotion regulation: Antecedents and well-being outcomes of cognitive reappraisal and expressive suppression in cross-cultural samples. *Journal of Happiness Studies: An Interdisciplinary Forum on Subjective Well-Being, 10*(3), 271–291. https://doi.org/10.1007/s10902-007-9080-3

Hebb, D. O. (1949). *The organization of behavior: A neuropsychological theory*. Chapman & Hall.

Heckhausen, J., & Schulz, R. (1995). A life-span theory of control. *Psychological Review, 102*(2), 284–304. https://doi.org/10.1037/0033-295X.102.2.284

John, O. P., & Gross, J. J. (2004). Healthy and unhealthy emotion regulation: Personality processes, individual differences, and life span development. *Journal of Personality, 72*(6), 1301–1334. https://doi.org/10.1111/j.1467-6494.2004.00298.x

Koole, S. L. (2009). The psychology of emotion regulation: An integrative review. *Cognition & Emotion, 23*(1), 4–41. https://doi.org/10.1080/02699930802619031

Labouvie-Vief, G., & Blanchard-Fields, F. (1982). Cognitive ageing and psychological growth. *Ageing and Society, 2*(2), 183–209. https://doi.org/10.1017/S0144686X00009429

Labouvie-Vief, G., DeVoe, M., & Bulka, D. (1989). Speaking about feelings: Conceptions of emotion across the life span. *Psychology and Aging, 4*(4), 425–437. https://doi.org/10.1037//0882-7974.4.4.425

Larcom, M. J., & Isaacowitz, D. M. (2009). Rapid emotion regulation after mood induction: Age and individual differences. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences, 64*(6), 733–741. https://doi.org/10.1093/geronb/gbp077

Lawton, M. P., Kleban, M. H., Rajagopal, D., & Dean, J. (1992). Dimensions of affective experience in three age groups. *Psychology and Aging, 7*(2), 171–184. https://doi.org/10.1037/0882-7974.7.2.171

Magerl, W., Hansen, N., Treede, R.-D., & Klein, T. (2018). The human pain system exhibits higher-order plasticity (metaplasticity). *Neurobiology of Learning and Memory, 154*, 112–120. https://doi.org/10.1016/j.nlm.2018.04.003

Manzoor, A., Abro, A. H., & Treur, J. (2017). Monitoring the impact of negative events and deciding about emotion regulation strategies. In N. Criado Pacheco, C. Carrascosa, N. Osman, & V. Julián Inglada (Eds.), *14th European Conference on Multi-Agent Systems, EUMAS'16. Lecture Notes in AI* (pp. 350–363). Springer International Publishing.

Nakagawa, T., Gondo, Y., Ishioka, Y., & Masui, Y. (2017). Age, emotion regulation, and affect in adulthood: The mediating role of cognitive reappraisal. *Japanese Psychological Research, 59*(4), 301–308. https://doi.org/10.1111/jpr.12159

Ostroumov, A., & Dani, J. A. (2018). Convergent neuronal plasticity and metaplasticity mechanisms of stress, nicotine, and alcohol. *Annual Review of Pharmacology and Toxicology, 58*, 547–566. https://doi.org/10.1146/annurev-pharmtox-010617-052735

Parkinson, B., & Totterdell, P. (1999). Classifying affect-regulation strategies. *Contition and Emotion, 13*(3), 277–303.

Phillips, L. H., Henry, J. D., Hosie, J. A., & Milne, A. B. (2006). Age, anger regulation and well-being. *Aging & Mental Health, 10*(3), 250–256. https://doi.org/10.1080/13607860500310385

Pruessner, L., Barnow, S., & Holt, D. (2020). V: Supplemental material for a cognitive control framework for understanding emotion regulation flexibility. *Emotion, 20*(1), 21–29. https://doi.org/10.1037/emo0000658.supp

Richards, J. M., & Gross, J. J. (2000). Emotion regulation and memory: The cognitive costs of keeping one's cool. *Journal of Personality and Social Psychology, 79*(3), 410–424. https://doi.org/10.1037/0022-3514.79.3.410

Robinson, B. L., Harper, N. S., & McAlpine, D. (2016). Meta-adaptation in the auditory midbrain under cortical influence. *Nature Communications, 7*(1), 13442. https://doi.org/10.1038/ncomms13442

Rothbart, M. K., Ahadi, S. A., & Evans, D. E. (2000). Temperament and personality: Origins and outcomes. *Journal of Personality and Social Psychology, 78*(1), 122–135. https://doi.org/10.1037/0022-3514.78.1.122

Scheibe, S., & Blanchard-Fields, F. (2009). Effects of regulating emotions on cognitive performance: What is costly for young adults is not so costly for older adults. *Psychology and Aging, 24*(1), 217–223. https://doi.org/10.1037/a0013807

Scheibe, S., & Carstensen, L. L. (2010). Emotional aging: Recent findings and future trends. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 65B*(2), 135–144. https://doi.org/10.1093/geronb/gbp132

Schultz, W., Dayan, P., & Montague, P. R. (1997). A Neural Substrate of Prediction and Reward. *Science, 275*(5306), 1593–1599. https://doi.org/10.1126/science.275.5306.1593

Sehgal, M., Song, C., Ehlers, V. L., & Moyer, J. R. (2013). Learning to learn—Intrinsic plasticity as a metaplasticity mechanism for memory formation. *Neurobiology of Learning and Memory, 105*, 186–199. https://doi.org/10.1016/j.nlm.2013.07.008

Sheppes, G. (2014). Emotion regulation choice: Theory and findings. In *Handbook of emotion regulation* (2nd ed., pp. 126–139). Guilford Press.

Sheppes, G., Scheibe, S., Suri, G., & Gross, J. J. (2011). Emotion-regulation choice. *Psychological Science, 22*(11), 1391–1396. https://doi.org/10.1177/0956797611418350

Sjöström, P. J., Rancz, E. A., Roth, A., & Häusser, M. (2008). Dendritic excitability and synaptic plasticity. *Physiological Reviews, 88*(2), 769–840. https://doi.org/10.1152/physrev.00016.2007

Treur, J. (2016). *Network-oriented modeling: Addressing complexity of cognitive, affective and social interactions*. Springer International Publishing.

Treur, J. (2019). Multilevel network reification: Representing higher order adaptivity in a network. In L. M. Aiello, C. Cherifi, H. Cherifi, R. Lambiotte, P. Lió, & L. M. Rocha (Eds.), *Complex networks and their applications VII* (pp. 635–651). Springer International Publishing.

Treur, J. (2020a). *Network-oriented modeling for adaptive networks: Designing higher-order adaptive biological, mental and social network models*. Springer Nature.

Treur, J. (2020b). Modeling higher-order network adaptation by multilevel network reification. In J. Treur (Ed.), *Network-oriented modeling for adaptive networks: Designing higher-order adaptive biological, mental and social network models* (pp. 99–119). Springer International Publishing.

Troy, A. S., Shallcross, A. J., & Mauss, I. B. (2013). A person-by-situation approach to emotion regulation: Cognitive reappraisal can either help or hurt, depending on the context. *Psychological Science, 24*, 2505–2514.

Ullah, N., Gao, Z., Liu, R., & Treur, J. (2020a). A second-order adaptive temporal-causal network model for age and gender differences in evolving choice of emotion regulation strategies. *Journal of Information and Telecommunication, 4*(2), 213–228. https://doi.org/10.1080/24751839.2020.1724738

Ullah, N., Koole, S. L., & Treur, J. (2020b). Take it or leave it: A computational model for flexibility in decision-making in downregulating negative emotions. In: Huang, De-Shuang, et al. (eds.) International Conferenec on Intelligent Computing, ICIC'20. p. 12. Springer Notes in Computer Science. Springer Nature, Switzerland.

Ullah, N., & Treur, J. (2019). The choice between bad and worse: A cognitive agent model for desire regulation under stress. In M. Baldoni, M. Dastani, B. Liao, Y. Sakurai, & R. Zalila

Wenkstern (Eds.), *Principles and practice of multi-agent systems. PRIMA 2019. Lecture notes in computer science* (pp. 496–504). Springer International Publishing.

Ullah, N., & Treur, J. (2020a). The older the better: A fourth-order adaptive network model for reward-driven choices of emotion regulation strategies over time. *Applied Network Science, 5*(27), 1–15. https://doi.org/10.1007/s41109-020-00267-1

Ullah, N., & Treur, J. (2020b). Better late than never: A multilayer network model using metaplasticity for emotion regulation strategies. In H. Cherifi, S. Gaito, J. F. Mendes, E. Moro, & L. M. Rocha (Eds.), *Complex Networks and Their Applications VIII. COMPLEX NETWORKS 2019. Studies in Computational Intelligence* (pp. 697–708). Springer International Publishing.

Ullah, N., & Treur, J. (2020c). How motivated are you? A mental network model for dynamic goal driven emotion regulation. In: The 19th International Conference on Artificial Intelligence and Soft Computing, ICAISC'20.

Ullah, N., & Treur, J. (2020d). Know yourself: An adaptive causal network model for therapeutic intervention for regaining cognitive control. In I. Maglogiannis, L. Iliadis, & E. Pimenidis (Eds.), *Artificial intelligence applications and innovations. advances in information and communication technology* (pp. 334–346). Springer International Publishing.

Ullah, N., Treur, J., & Koole, S. L. (2018). A computational model for flexibility in emotion regulation. In A. V. Samsonovich & C. J. Lebiere (Eds.), *Postproceedings of the 9th Annual International Conference on Biologically Inspired Cognitive Architectures, BICA 2018* (pp. 572–580). Elsevier B.V.

Vose, L., & Stanton, P. (2017). Synaptic plasticity. *Metaplasticity and Depression. Current Neuropharmacology, 15*(1), 71–86. https://doi.org/10.2174/1570159X14666160202121111

Webb, T. L., Miles, E., & Sheeran, P. (2012a). Dealing with feeling: A meta-analysis of the effectiveness of strategies derived from the process model of emotion regulation. *Psychological Bulletin, 138*(4), 775–808. https://doi.org/10.1037/a0027600

Webb, T. L., Schweiger Gallo, I., Miles, E., Gollwitzer, P. M., & Sheeran, P. (2012b). Effective regulation of affect: An action control perspective on emotion regulation. *European Review of Social Psychology, 23*(1), 143–186. https://doi.org/10.1080/10463283.2012.718134

Yeung, D. Y., Wong, C. K. M., & Lok, D. P. P. (2011). Emotion regulation mediates age differences in emotions. *Aging & Mental Health, 15*(3), 414–418. https://doi.org/10.1080/13607863.2010.536136

Zegerius, L., & Treur, J. (2020). Modelling metaplasticity and memory reconsolidation during an eye-movement desensitization and reprocessing treatment. pp. 1–21.

Zimmermann, P., & Iwanski, A. (2014). Emotion regulation from early adolescence to emerging adulthood and middle adulthood. *International Journal of Behavioral Development, 38*(2), 182–194. https://doi.org/10.1177/0165025413515405

Chapter 12
A *Dynamic Affective Core* to Bind the Contents, Context, and Value of Conscious Experience

Kenneth T. Kishida and L. Paul Sands

Abstract The private and dynamic nature of conscious subjective experience poses an empirical challenge that has led neuroscience-based theories about consciousness to note the importance of ‘the hard problem’ of explaining how subjective phenomenal experience can arise from neural activity but set it aside and focus on the ‘easier’ problems associated with information representation and behavior. This approach leaves a major gap in our understanding of the neural mechanisms underlying conscious subjective experience and its dynamic nature. However, computational methods integrated with a variety of tools for measuring human brain activity are beginning to link dynamic changes in subjective affect with reproducible neurobehavioral signals in humans. In particular, research applying computational reinforcement learning theory has shown tremendous utility in investigating human choice behavior and the role the dopaminergic system plays in dynamic behavioral control. This research is beginning to reveal an explicit connection between the dynamics of dopaminergic signals and dynamic changes in subjective affect. However, it should be obvious that the dopaminergic system alone is not sufficient to explain all of the complexities of affective dynamics. We review foundational work, highlight current problems and open questions, and propose a *Dynamic Affective Core Hypothesis* that integrates advances in our understanding of the rep-

---

K. T. Kishida (✉)
Department of Physiology and Pharmacology, Wake Forest School of Medicine,
Winston-Salem, NC, USA

Department of Neurosurgery, Wake Forest School of Medicine, Winston-Salem, NC, USA

Neuroscience Graduate Program, Wake Forest School of Medicine,
Winston-Salem, NC, USA
e-mail: kkishida@wakehealth.edu

L. P. Sands
Neuroscience Graduate Program, Wake Forest School of Medicine,
Winston-Salem, NC, USA
e-mail: lsands@wakehealth.edu

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_12

resentation of the content and context of conscious experiences with our nascent understanding about how these representations acquire and retain affective subjective value.

Keywords Consciousness · Reinforcement learning · Dopamine · Serotonin · Norepinephrine · Reward prediction error · Subjective experience · Qualia

12.1 Introduction

In "What is it like to be bat?" (Nagel, 1974), Nagel highlights the gap in our ability to provide a mechanistic account of subjective phenomenal experience from our current knowledge about nervous systems. In a related vein, Chalmers (1996) coined the distinction between 'easy' problems and 'the hard problem' facing investigations about how physical processes generate subjective phenomenal experience (i.e., *qualia*). The '*easy problems*' are those for which it is conceivable that we will find solutions given the currently known mechanistic working of neural processes; the '*hard problem'* concerns an explanation of how the physical processes could possibly give rise to subjective phenomenal experiences *a priori*. Leading neuroscientific theories about consciousness note the importance of subjective phenomenal experience but set this 'hard problem' aside to instead focus on the 'easy problems' regarding how nervous systems represent information and control behavior (Edelman & Tononi, 2000; Crick & Koch, 2003). In line with others' 'faith' in a scientific approach (Churchland & Churchland, 2002; Churchland, 2005), we reject this distinction. The 'hard problem' is hard, but not in any special way that prevents scientific investigation. Instead, it represents the most exciting frontier in human neuroscience research. Before we had an empirically based theory of electromagnetism, electricity and magnetism must have seemed magical and fundamentally unexplainable (through known physical mechanism) to philosophers of the time. But, through rigorous empirical investigation and the development of supporting mathematical theory, major breakthroughs came in our understanding of a fundamental physical phenomenon (Forbes & Mahon, 2014). We believe that (broadly) neuroscience research had simply not focused its attention, until recently, to the problem of conscious subjective experience in humans. These tides are changing, and advances in seemingly disparate areas of research are poised to come together through applications of mathematical theory to begin to shed light on how a nervous system could give rise to subjective phenomenal feeling.

'Affective dynamics'—and particularly computational approaches thereof (Cunningham et al., 2013)—represent an investigative construct well-suited to push past the current boundaries of neuroscience research about dynamic changes in emotion-related behavior and move towards a neuroscience of consciousness squarely focused on mechanisms giving rise to subjective phenomenal experience. Presently, much of the work can be framed into two (admittedly overbroad) domains of research: (1) investigations into the role of reinforcement learning in driving dynamic changes in behavior and associated reports about subjective emotional reactions, and (2) investigations into the roles of functional networks involving cortical and sub-cortical brain regions in dynamically representing emotion. While both domains of research are in and of themselves rich and highly productive, little has been done to bridge the divide between them and provide a mechanistic account of the dynamics underlying how changes in the environment or behavioral state of an individual induce changes in the functional networks representing the vast range of observable, dynamic emotional reactions and associated subjective experiences.

Here, we discuss a framework for investigating affective dynamics that is founded on computational reinforcement learning theory (Sutton & Barto, 1998) and its tight connection to the neurobiology of adaptive behavior. We review the dominant theory for dopamine neuron function (as a generator of a "temporal difference reward prediction error" signal) and its role in behavioral control and value updating (Montague et al., 1996; Schultz et al., 1997; Montague et al., 2004; Glimcher, 2011; Watabe-Uchida et al., 2017). We review how this framework has, to date, been used to investigate affective dynamics, but also this approach's dopamine-centric limitations. We follow this discussion with (1) an extension of temporal difference reinforcement learning theory to include a parallel system hypothesized to support *temporal difference aversive learning*; (2) the interaction of these parallel appetitive-learning and aversive-learning systems to generate valuation and salience signals; and (3) evidence that these valuation and salience signals are fundamental to dynamic affective experience. We briefly discuss a candidate set of key neural structures that we hypothesize are necessary components of a dynamic network for representing emotion, and we describe how ascending valuation systems (e.g., dopamine- and serotonin-releasing neurons) are integral to this network. We discuss how this network relates to the *dynamic core* hypothesis that was proposed by Edelman and Tononi (2000) to explain consciousness—in particular, we note that their notion of a *dynamic core* did not necessitate key elements, and the consequences of these omissions. Crucially, we believe that Edelman and Tononi's 'dynamic core' appears sufficient for an integrated representation of the contents and context of dynamically evolving conscious experiences, but it omits systems required to provide those representations affect and value. Thus, we introduce the Dynamic Affective Core hypothesis, which updates the original dynamic core hypothesis to now necessarily include originally omitted affect and valuation systems. We discuss the implications of the Dynamic Affective Core hypothesis and future directions for this line of research.

12.2 Affective Dynamics as a Phenomenon Resulting from Systems Seeking 'Optimal Control'

Moment-to-moment changes in one's emotional state can be driven by external and internal signals. The environment naturally evolves, and an organism's nervous system ought to track this evolution with its own evolving representations of the environment in parallel with representations of its own evolving internal states (e.g., proprioceptive body position, body temperature, energy levels, etc.). Associated with these objective quantities are affective, subjective feelings (e.g., hunger, thirst, pain, and pleasure). These representations are in turn used to guide adaptive physiological responses and behavior. How nervous systems accomplish this can be investigated through a computational framework (Minsky, 1967) where the actual "state of an agent" and the actual "state of the environment" can be represented explicitly, as can their interactions. Further, *representations* of the state of an agent and the environment can be explicitly represented as hypothetical physical states that nervous systems may instantiate. Within such a framework, one can consider that as the state of the agent and external environment continuously evolve, the affective state of the agent is expected to also continuously evolve. We hypothesize that the representation of exteroceptive and interoceptive state-transitions is associated with representations of the affective emotional valence (i.e., subjective value) of these experienced states and actions. This dynamic evolution of emotional subjective experience is the target of our investigation. To be rigorous in our approach, we employ a computational framework to aid in making explicit our assumptions and hypotheses about the dynamic mechanisms at play.

Artificial intelligence research has developed theory around how the behavioral problem (e.g. how to choose how to act and adapt behavior) may be solved with an eye towards optimal solutions. One particularly successful line of reasoning has led to the development of computational reinforcement learning theory (Sutton & Barto, 1998, 2018). Within artificial intelligence research, computational reinforcement learning theory has been used as a core theoretical construct to explore how emotions may be integrated into the decision-making processes of computational (artificially intelligent) agents (surveyed in Moerland et al., 2018). More specific to our line of inquiry is recent empirical work bridging computational reinforcement learning theory and human neuroscience that is beginning to connect dopamine neuron activity with how the human brain dynamically adapts not only representations of states and actions, but also representations of associated subjective experiences (Xiang et al., 2013; Rutledge et al., 2014; Eldar & Niv, 2015).

12.2.1 Computational Reinforcement Learning Theory and Dopamine

Computational Reinforcement Learning (RL) theory (Sutton & Barto, 1998, 2018) provides an explicit framework to investigate processes involved when a theoretical agent makes decisions under uncertainty, experiences the consequences of those decisions, and makes changes in its approach (i.e., learns) to make 'better' decisions in the future. This theoretical framework assumes that the *agent* seeks to maximize the 'reward' it attains and builds from this fundamental assumption a mathematical rendering that incorporates theory about Finite Markov Decision Processes, Dynamic Programming, and Monte Carlo Methods (see Sutton & Barto, 1998 and a revised edition in 2018 for an authoritative textbook on how these ideas are brought together). Importantly, the agent in question is an abstract computational agent—not necessarily a biological one, let alone human. This approach simply seeks to find computable optimal solutions to behavioral control and, when such computations are intractable, to determine best estimates for these solutions (Bach & Dayan, 2017). Moerland and colleagues (Moerland et al., 2018) have recently provided an extensive survey of how these ideas have been explored to incorporate models of 'emotions' into various learning algorithms in AI research. Moerland's survey provides a wide range of hypotheses about how emotions may be represented in adaptive reinforcement learning algorithms, but empirical support that these proposals are actually implemented biologically remains lacking. On the other hand, Montague and colleagues' publication in 1996 (Montague et al., 1996) demonstrated that dopamine neurons in non-human primates encode a key signal in reinforcement learning theory—a *temporal difference reward prediction error*. This finding has since been a foundation for research into the basis of adaptive decision-making in humans (and non-human animals) and more recently in investigations about the neural basis of dynamic changes in subjective experience in humans.

Temporal Difference Reinforcement Learning is a foundational idea that grew out of computational reinforcement learning theory research. The basic idea is as follows—it is assumed that an agent always seeks to maximize the attainment of 'reward'. To do so, it must learn the value of various states and actions that it finds itself in and that it has available to it at any given time, respectively. The 'Value' (V_t) of a particular state at a given time (t), in this context, is simply the sum of the reward currently acquired (r_t) plus the rewards the agent may attain in the future given that it finds itself in that state ($r_{t+1} + r_{t+2} + r_{t+3} + \ldots$), so:

$$V_t = r_t + r_{t+1} + r_{t+2} + r_{t+3} + \ldots + r_{t+T} \tag{12.1}$$

We can modify this estimate by incorporating a discounting of future (not yet acquired) rewards:

$$V_t = \gamma^0 r_t + \gamma^1 r_{t+1} + \gamma^2 r_{t+2} + \gamma^3 r_{t+3} + \ldots + \gamma^T r_{t+T} \tag{12.2}$$

Here γ is a parameter that is greater than zero, less than one, and therefore shrinks exponentially small when raised to increased powers towards T. This causes proximate rewards to be weighted more heavily than distant future rewards. The challenge for the agent (with incomplete knowledge of the future) is to estimate this value function for any given state it may find itself in. Learning (better estimates of V_t) proceeds through experience (real or simulated) where prediction *errors (δ)* about the estimated expected value are used to update (i.e., make corrections to) the estimated expected value:

$$V_t' \leftarrow V_t + \alpha \delta_t \tag{12.3}$$

In Eq. (12.3), V_t on the right-hand side is changed to V_t' by an amount δ_t (*i. e.* ,the reward prediction error) modulated by the learning rate α. Small fractional changes

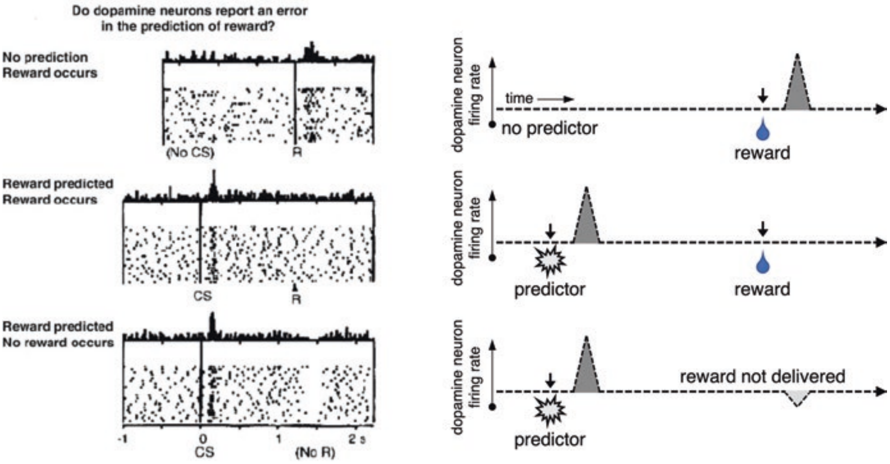


Fig. 12.1 Dopamine neurons encode temporal difference reward prediction errors. Dopamine neurons change their rate of firing in a manner consistent with 'temporal difference reward prediction errors'. Left: Recordings of dopamine neuron spike rates during the presentation of rewards (squirts of juice) and a conditioning stimulus (e.g. flash of light); figure panel adapted from Schultz, Dayan, and Montague (1997). Right: Cartoon depiction of dopamine neuron behavior in the different phases of learning depicted in left panel. Top row: Prior to learning, dopamine neurons increase their firing rate in response to unexpected delivery of reward. Middle row: After conditioning, with consistent pairing of a predictive stimulus and a reward, dopamine neurons increase their firing rate to the predictive stimulus and do not change their firing rate when the reward is delivered as expected. Bottom row: After conditioning, dopamine neurons increase their firing rate to the predictive stimulus and go silent (firing rate goes to zero) when the expected reward is not delivered

in α lead to slower learning, whereas larger α causes δ_t to have a bigger influence. In *temporal difference reinforcement learning*, the errors—called *temporal difference reward* prediction errors (δ_t)—are calculated as follows:

$$\delta = \left(r_t + \gamma V_{t+1}\right) - V_t \tag{12.4}$$

Note that these errors are determined by incorporating not only the experienced reward in the current state (at time "t": r_t), but also a discounted estimate of future rewards (γV_{t+1}); combined, these two terms (($r_t + \gamma V_{t+1}$)) are compared to the current estimate of value (V_t) and the difference is the "temporal reward prediction error". This reward prediction error term has been hypothesized and demonstrated to be encoded by dopamine neuron activity in non-human primates (Fig. 12.1: Montague et al., 1996; Schultz et al., 1997; Bayer & Glimcher, 2005; reviewed in Glimcher, 2011; for a historical account: Colombo, 2014; Watabe-Uchida et al., 2017) and to be consistent with temporal dynamics of blood oxygen level dependent responses (measured with functional magnetic resonance imaging) in regions of the human brain that are highly innervated by dopamine releasing terminals (Pagnoni et al., 2002; Montague et al., 2006).

The first association between the temporal difference reward prediction error and non-human primate dopamine neuron activity was shown in Montague et al. (1996) and reviewed in the context of prior work in Schultz et al. (1997). Subsequently, the role of reward prediction errors and dopaminergic signaling in mammalian decision making grew into a highly impactful field of research (reviews: Montague et al., 2004; Glimcher, 2011; Colombo, 2014; Watabe-Uchida et al., 2017), with elaborations on this basic framework revealing a consistent role for reward prediction error signals guiding human and animal behavior during a wide variety of experimental paradigms that require these agents to make incentivized decisions under uncertain conditions.

A number of predictions from this basic formulation have been tested and the overarching hypothesis upheld, though recent work has challenged the completeness of this idea in humans (Kishida et al., 2011, 2016; Moran et al., 2018; Bang et al., 2020). The *"temporal difference reward prediction error"* (Eq. 12.4) *hypothesis* for dopamine neuron activity, expressed in words, predicts: (1) increases in DA neuron spike activity (from background rates) when "things are better than expected", (2) decreases when "things are worse than expected", and (3) no change when "things are just as expected". In this interpretation, dopamine neurons are always emitting information to downstream neural structures since even no change in firing rate carries meaning. This computational hypothesis is strongly supported by the *timing* and *amplitude* of burst and pause responses in the spike trains of dopamine neurons (Montague et al., 1996; Schultz et al., 1997; Fiorillo et al., 2003; Montague et al., 2004; Bayer & Glimcher, 2005; Dayan and Niv, 2008; Watabe-Uchida et al., 2017). Further, this hypothesis appears to be supported (at least in part) by dopamine release measurements in rodents (Hart et al., 2014; Clark et al., 2010), single unit recordings of dopamine neurons in humans (Zaghloul et al., 2009), and direct measurements of dopamine release in humans (Kishida et al., 2016; Moran et al., 2018).

Note, however, that in Kishida et al., 2016 and Moran et al., 2018 it was demonstrated that sub-second changes in dopamine levels in human striatum are not fully explained by the simple reward prediction error hypothesis. In these experiments, extracellular dopamine release was measured in humans with sub-second temporal resolution during a sequential monetarily incentivized decision-making task (Kishida et al., 2011, 2016). While these measurements were made, participants performed a stock market gambling task that elicited reward prediction errors about the participants' investment decisions and market fluctuations. Importantly, participants' investments were lodged as percentages of their continuously updated portfolio. Thus, counterfactual information—what "could have been" had they chosen to invest more or less than they actually did—was present on every trial. Kishida et al., 2016 demonstrated that sub-second dopamine fluctuations in the striatum integrated the reward prediction error term with a counterfactual prediction error term (Fig. 12.2). In other words, dopamine fluctuations in response to better- or worse-than-expected outcomes (i.e., reward prediction errors) were depressed or even inverted according to the magnitude of missed gains or avoided losses had the participants invested one-hundred percent of their portfolio. In this sense, measured

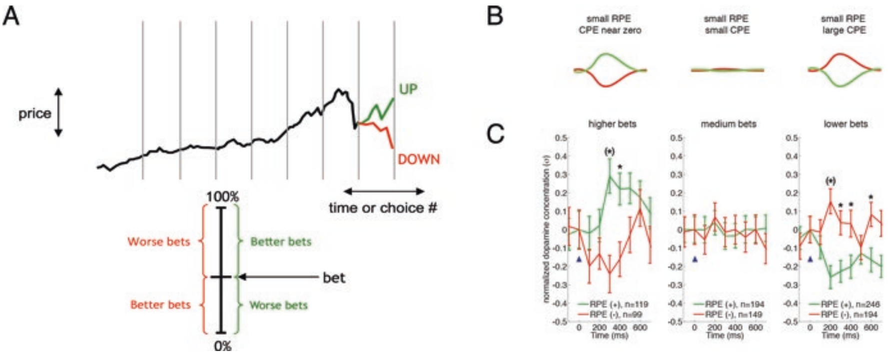


Fig. 12.2 Dopamine release in human striatum encodes superposed *reward prediction errors* and *counterfactual prediction errors*. Direct recordings of dopamine release during a sequential decision-making task (**a**) demonstrates that dopamine release encodes reward reward prediction errors (left columns of **b** and **c**), but that counterfactual information diminishes or inverts dopaminergic encoding of reward prediction errors about actual experience (middle and right columns of **b** and **c**). Figure panels adapted from Kishida et al. (2016). (**a**) Sequential investment game: Participants 'invest' into a stock market by lodging bets as a percentage of their portfolio. Market returns increase or decrease the participant's portfolio as a function of the percent invested and the percent change in the stock price. For market increases and decreases, the amount not invested represent missed gains or avoided losses, respectively. These counterfactual outcomes are observed to modulate dopamine (panel **c**) and serotonin (Moran et al., 2018) responses to reward prediction errors over actual gains and losses in the game. (**b** and **c**) Model predictions (**b**) and actual dopamine responses (**c**) for a model that integrates 'reward prediction errors' and 'counterfactual prediction errors'. Green: dopamine responses (predicted (**b**) or observed (**c**)) to positive reward prediction errors. Red: dopamine responses (predicted (**b**) or observed (**c**)) to negative reward prediction errors. Left column: Counterfactual outcomes are minimized (investments near 100%) and the dopamine response is positive for positive reward prediction errors and negative for negative reward prediction errors (as predicted by the traditional reward prediction error hypothesis). Middle and Right columns: As the bet sizes decrease, the counterfactual terms increase and diminish (middle column) or invert (right column) the dopamine response to positive and negative reward prediction errors. Figure panel (**c**) adapted from Kishida et al. (2016)

fluctuations in dopamine levels within ~700 ms following an outcome corresponded with how participants *ought* to have felt: *positive feelings about better-than-expected outcomes* would be muted or even inverted to negative feelings when regret (over not investing more) increases, and *negative feelings about worse-than-expected outcomes* would be muted or inverted to positive feelings when relief is high (Fig. 12.2, 'regret' and 'relief' would increase with decreasing bet size). In a follow up study, Moran and colleagues extended the work and demonstrated that serotonin fluctuations in human striatum encoded an opponent response to the dopamine signal, suggesting that dopamine and serotonin are, together, critical in the processing of actual and counterfactual reward prediction errors in sequential decision-making processes. Unfortunately, however, subjective assessments were not performed in these experiments, so the connection between sub-second dopamine and serotonin release and subjective experience remains hypothetical.

The hypothesis that dopamine fluctuations encode fluctuations in positive affect may seem obvious, given that dopamine neurons and extracellular dopamine levels dynamically encode "reward" prediction errors. This is consistent with pleasure and subjective well-being focused emotion literature connecting these emotions and related processes to dopamine's function (Kringelbach & Berridge, 2017). However, it is important to note that the term "reward" in the naming of this error term does not *explicitly* mean the "subjective experience of reward". Rather, this term refers to a quantity that a computed objective function aims to maximize, and its connection to subjective reward is only implied or useful as an analogy when thinking about related computer algorithms from an anthropomorphic perspective. The explicit relationship between reward prediction errors, dopamine, and dynamic changes in human subjective experience has only recently begun to be explored.

12.2.2 Reinforcement Learning and Affective Dynamics

The formal framework of computational reinforcement learning provides a rich landscape for investigating how the brain may generate dynamic changes in emotional behavior and subjective experience (Doya, 2000; Xiang et al., 2013; Eldar et al., 2016; Bach & Dayan, 2017; Huys & Renz, 2017; Moerland et al., 2018). For example, the development and implementation of computer agents that use modified reinforcement learning algorithms to incorporate intuited features of emotion can generate a wide spectrum of hypotheses about how the human brain may 'compute' and generate emotional behaviors with the goal of augmenting artificial intelligence behavior (Moerland et al., 2018). While this approach notes the connection between reinforcement learning and hypothesized neural processes, their primary focus on machine learning applications is less constrained by or interested in solving the biological question and more concerned with the augmentation of machine learning algorithms. Implementation of 'emotion algorithms' in artificial intelligence solutions may in some cases be feasible only *in silico* and for certain problems. In this vein, computer and decision scientists discover solutions to optimize learning and decision making that may not be possible for biological agents that are strictly constrained by limited time and energy, high uncertainty environments, and constant threats to existence (Montague, 2006; Bach & Dayan, 2017; Huys & Renz, 2017). Here, it must be assumed that evolution has shaped the mechanisms underlying emotion-related modifications to behaviors and associated subjective experience. Thus, empirical work (in conjunction with theory) is necessary to discover how the human brain solves the decision-making problem and generates associated subjective experiences. Computational neuroscientists trying to discover how emotions are generated are beginning to investigate how neuromodulatory systems (e.g., dopaminergic, serotonergic, and noradrenergic neurons) drive not only learning and arousal states, but also affective dynamics, mood, and emotion regulation (Doya, 2002; Etkin et al., 2015; Eldar et al., 2016; Huys & Renz, 2017; Bach & Dayan, 2017).

One of the first demonstrations that reward prediction errors modulate self-reports about subjective feelings came from work investigating social exchange (Xiang et al., 2013). In this work, Xiang and colleagues had participants play the ultimatum game repeatedly, but with different partners. In the ultimatum game, a proposer is given a set amount of money and proposes a split of the money between themselves and a partner. The partner then has the choice of accepting the split or rejecting the offer, knowing that a rejection means that both players will receive nothing (Fehr & Gächter, 2002; Camerer, 2003). In Xiang et al., the participants were the partners receiving the offered splits and the proposers were computer agents programmed to give similar distributions of offers and to shift their proposals (as a group) halfway through the task. In this manner, participants received offers that at first may be low or high, but common to the group, and a 'social norm' learned. Deviations about this norm generated prediction errors about the expected offer value, which were exaggerated when 'the group' shifted its behavior mid-way through the task. Participants playing this task were instructed that they would be playing with partners that were all different and independent. Occasionally, participants were probed about 'how they felt' about the most recent offer. Xiang et al., report that subjective feelings correlated with the norm prediction error and that the norm prediction error correlated with fMRI measured BOLD responses in the orbital frontal cortex (Xiang et al., 2013). Additionally, BOLD responses to the norm prediction error were observed in the dorsal and ventral striatum, and bilateral anterior insula.

Eldar and colleagues (Eldar et al., 2016) review recent applications of a reinforcement learning framework and gambling tasks to investigate affective dynamics and mood and hypothesize how the proposed computational models may be used to better understand mood disorders. Two key studies form the basis of their argument (Rutledge et al., 2014; Eldar & Niv, 2015). Rutledge et al. (2014) investigated emotional reactivity in response to a probabilistic reward task that did not require participants to estimate the expected values of choices presented through learning. Expected values could be calculated on the spot (per trial) with complete information about the risks associated with either a gamble or an alternative 'sure bet'. They demonstrated that dynamic changes in "momentary happiness" were explained by a non-linear combination of expected values and associated reward prediction errors over a short history of recent trials. Further, they used fMRI to show that BOLD responses in the striatum tracked the same task variables that predicted subjective happiness ratings. Together, these findings strongly implicate a role for parameters estimated using computational reinforcement learning theory (e.g. expected value and reward prediction errors) and the dopaminergic system (i.e., dorsal and ventral striatal activation to reward prediction errors). in modulating subjective human feelings. Importantly, striatal BOLD imaging signals that track computed reward prediction errors are only circumstantial evidence that these signals are in fact delivered by dopamine neuron activity—BOLD imaging tracks physiological activity that consumes oxygen in the blood and cannot alone distinguish activity specifically driven by dopamine release.

Eldar and Niv (2015) used a computational reinforcement learning framework to investigate a hypothesized bidirectional interaction between the 'evaluation of outcomes' and 'changes in emotional state', and how the latter impacts the evaluation of future outcomes. Participants played a series of probabilistic slot machine games before and after a "wheel-of-fortune" draw that resulted in a surprising large magnitude outcome. The impact of the wheel-of-fortune draw went as one might expect—improved mood for a big win and decreased mood for big losses, but the impact of mood was also measured on the outcomes of the subsequent smaller outcome slot machine games. They showed that large magnitude outcomes on the wheel-of-fortune game colored the outcomes of the subsequent slot machine games. Again, a role for dopamine was implicated by the demonstration of striatal BOLD responses to reward prediction errors following wins in the slot machine games. Interestingly, the impact of the wheel-of-fortune outcome on striatal responses to the slot machine game outcomes differentiated those participants who had an increased hypomanic personality. The authors then demonstrate within a reinforcement learning framework that they could account for and predict the behavioral observation that mood instability was associated with a positive feedback loop where big changes in mood altered the perception of outcomes in subsequent slot machine games. Together, the results of their study implicate dopaminergic learning signals in modulating dynamic changes in affect, a process that may become destabilized in people with increased mood instability.

Another study that has embraced the reinforcement learning framework to investigate the impact of emotional outcomes on future decisions was performed by Katahira and colleagues (2015). Many studies have used monetary incentives to demonstrate the interaction of estimates of expected value, reward prediction errors, and human decision-making. The advantage of monetary incentives is the inherent quantitative nature of the reinforcer, so incorporating money as the reward in the reinforcement learning framework is relatively straightforward. Katahira and colleagues tackled an important problem in a creative way. They asked whether decision-making under uncertainty where emotional outcomes (that are inherently subjective) could be modeled and understood in the quantitative reinforcement learning framework. Here they employed a probabilistic "reward and punishment" task where, instead of money, participants received feedback in the form of subjectively pleasant or unpleasant pictures, respectively. Images were drawn from the international affective picture system data base (Lang et al., 2007). While the categories of pleasant, neutral, or unpleasant images could be estimated *a priori* from the IAPS database, it is unclear what the motivational value of each image would be per participant. Typically, in reinforcement learning modeling, the learning rate (α) and future discount rate (γ) are estimated as free parameters while fitting the models to participant behavior. Katahira and colleagues allowed the 'motivational value' of each image category to also be a free parameter and could thus estimate from behavior a quantity that would otherwise be a private subjective value. They compared behavioral and brain responses fit to reinforcement learning models for this task to a monetarily incentivized task modeled in a similar manner and demonstrated both appetitive and aversive prediction errors in the striatum for both the emotionally evocative task and the monetarily incentivized task. Other co-activated regions included bilateral insula and precuneus.

Model-based reinforcement learning algorithms have been used to explore how emotion regulation via (re)appraisal processes may be implemented in neural systems (Etkin et al., 2015; Huys & Renz, 2017). Model-based (versus model-free) reinforcement learning refers to an approach wherein the decision-making agent uses a model of the environment to speed learning. If a model of the environment is available, an agent can use it to simulate experiences and significantly enhance the rate of learning compared to solely experience-dependent (i.e., model-free) algorithms (Sutton & Barto, 1998, 2018). There is plenty of evidence that suggests humans (and other biological agents) use such models in their decision-making. Yet, the physical manifestation in neural systems of these representations and simulated experiences remains up for clarification. Nevertheless, model-based algorithms serve as an excellent framework to investigate mechanisms supporting emotion regulation or control. Etkin and colleagues (Etkin et al., 2015) have proposed the use of model-based reinforcement learning to unify diverse findings about the neural structures involved in the spectrum of emotion regulation strategies. In their framework, emotions are generated as part of the typical value-based decision-making process, whereas regulation of these emotions are thought of as meta to the generation process: 'actions' taken by the emotion regulation system are themselves 'decided' upon within a value-based decision-making process that adjudicates between the value of different state-action pairs representing emotion states and associated behavioral repertoires. They argue for a spectrum of model-based to model-free strategies for emotion regulation and suggest key differences in neural network dynamics that support each strategy. In a similar manner, Huys and Renz argue for the need of meta-reasoning over a model-based valuation framework to account for the nature of emotional appraisals and the flexibility of emotional responses.

The strengths of using a computational reinforcement learning framework to investigate mechanisms supporting affective dynamics include the formal nature of the description of its algorithms (Bach & Dayan, 2017; Huys & Renz, 2017) and the flexibility to explore variations on the core theme (Moerland et al., 2018). The exploration of methods to incorporate 'emotion computations' into reinforcement learning in artificial intelligence research (e.g., Moerland et al., 2018) provides a likely never-ending stream of 'thought experiments' that may or may not be relevant to the biology of human emotions. Accordingly, research that constrains the space of possible solutions using empirical results is necessary.

12.2.3 Limitations of 'Dopamine/TD-Reward': Centric Models

Over the last two and a half decades, the success in applying computational reinforcement learning algorithms to elucidate the neurobiological basis of human (and non-human animal) decision-making has been fueled by the singular demonstration that dopamine neurons encode the temporal difference reward prediction error (Fig. 12.1 and Eq. 12.4; Montague et al., 1996; Schultz et al., 1997). The empirical results discussed above that relate reinforcement learning to human affective dynamics all have the reward prediction error and dopamine's hypothesized role at their core. This core concept served as an anchor in these early days, but there are significant challenges to this construct that must be overcome. Dopamine neurons signal temporal difference reward prediction errors by emitting a burst (an increase in firing rate for positive reward prediction error), pause (halt in firing rate for negative reward prediction error), or no change (reward prediction error equals zero) in activity (Fig. 12.1, Montague et al., 1996; Schultz et al., 1997; Watabe-Uchida et al., 2017). This asymmetry poses a problem for encoding aversive input—a missed reward and a loss of any magnitude would be treated the same: a pause in dopamine neuron activity. This means that a dopamine neuron-centric system (acting in this manner) cannot parametrically encode aversive prediction errors. Likewise, theories of emotion that rely only on the dopaminergic system do not appear to be able to account for subjective feelings in the negative domain, but instead focus largely on the positive dimensions like pleasure (Kringelbach & Berridge, 2017).

Further, there is now a significant body of literature that suggests that dopaminergic signaling may be more complex (Bromberg-Martin et al., 2010; and Lammel et al., 2014; Watabe-Uchida et al., 2017). Electrophysiological (and more recently optical) recordings of putative dopamine neurons in the VTA and SN (in nonhuman primates and rodents) during a variety of behavioral task demands provide evidence that dopamine neurons respond to a wide range of positive, negative, and neutral stimuli. This may not be surprising given the significant heterogeneity in the molecular, cellular, and neuroanatomical characteristics that differentiate dopamine neurons (Watabe-Uchida et al., 2012; Lammel et al., 2014; Beier et al., 2015; Lerner et al., 2015; Gantz et al., 2018).

As such, a large number of signals have been proposed to be encoded by dopamine neurons. One parsimonious way to frame these signals is to split them into 'positive' (or at least neutral) and 'negative' valence categories. We start with the positive or neutral valence category of signals as these responses may be seen as an extension of the foundational notion that dopamine neurons encode TD-error signals that, as has been discussed, may be associated with primary rewards or also predictors (e.g., context and cues) of those rewards (Montague et al. 1996; Schultz et al., 1997). Then we will review and discuss the more controversial implications of dopamine neuron encoding of aversive or negatively valent stimuli.

12.2.4 Dopaminergic Response to Novelty and Surprise…

Some of the earlier evidence that suggested dopamine neurons encoded more than just a TD reward prediction error came from neural recordings in non-human primates (reviewed in Bromberg-Martin et al., 2010). In these experiments, it was shown that putative (electrophysiologically characterized) dopamine neurons responded in a brief burst in activity to surprising sensory events. These signals were diminished if the sensory stimulus became predictable and were absent when the animal was asleep (Takikawa et al., 2004; Strecker & Jacobs, 1985; Steinfels et al., 1983). These signals also appeared to be sensitive to the attentional demands of competing tasks, in that the 'alerting response' (following Bromberg-Martin et al., 2010) in dopamine neurons to unanticipated sensory stimuli could only be elicited when the animal was in a passive resting state, not engaged in a more highly-valued, goal-directed activity (Strecker & Jacobs, 1985; Horvitz et al., 1997; Horvitz, 2002).

This idea that a subset of dopamine neurons respond to surprising stimuli or novelty (Ljungberg et al., 1992) has been supported by more recent work in rodents (Menegas et al., 2017). Here, Watabe-Uchida and colleagues used fiber-fluorometry to monitor dopamine axons across the striatum. They observed differences in the dopaminergic response to novel cues when they compared responses in the ventral striatum and the posterior tail of the striatum. Importantly, these responses were monitored in mice performing a classical conditioning task where the reward prediction error hypothesis could be tested. Dopamine responses in the posterior tail of the striatum responded strongly to novel cues, whereas the dopamine response in the ventral striatum did not—at least not until the novel cue was reliably paired with a reward. Like the data generated in nonhuman primates, the dopamine responses (in the posterior tail of the striatum) to novel cues diminished with experience, but these responses also occurred tied to a variety of stimuli including rewarding, aversive, and neutral sensory stimuli (Menegas et al., 2017). Additionally, Menegas and colleagues were also able to show two important controls for these responses within the same experimental paradigm: (1) specificity of dopamine neuron activity through genetic control over the reporter, but also (2) that reward prediction errors could explain the activity observed in the ventral striatum-projecting dopamine neurons, but could not explain the activity in the posterior tail of the striatum.

Interestingly, it has been reported that dopamine neurons in the VTA can promote wakefulness and arousal (Eban-Rothschild et al., 2016; Taylor et al., 2016), and that a class of putative dopamine neurons residing in the dorsal raphe are activated by salient stimuli and, in so doing, also promote arousal and wakefulness (Lu et al., 2006; Cho et al., 2017). These latter cells are atypical in that most investigations of dopaminergic activity focus on the main populations of dopamine neurons found in the VTA and SN.

12.2.5 Dopaminergic Responses Regarding Context and Information…

'New, potentially informative sensory stimuli' is one way to characterize "novel" or "surprising" cues. Along these lines, it has also been shown that dopamine neurons will respond as though they detect changes in the sensory features of rewards

(Takahashi et al., 2017), can be modulated by changes in context (Nakahara et al., 2004), and can respond preferentially to sensory signals that provide advance information (Bromberg-Martin & Hikosaka, 2009).

Schoenbaum and colleagues (Takahashi et al., 2017) recorded single-unit activity of putative dopaminergic neurons in rats during an odor-guided choice task. In this task, odors signaled the availability of vanilla or chocolate milk of varying quantities. They were able to demonstrate that the rats showed no distinguishable preference for chocolate or vanilla flavoring, but did track the quantitative value (quantity of milk) delivered. The recorded dopamine neurons tracked the prediction error of the value association (reward prediction errors over the quantity of milk delivered). But also, notably, when the flavor of the reward delivered was different from what was expected (vanilla instead of chocolate, or vice-versa), dopamine neurons showed an additional burst in activity. This was true even when the quantity of milk was the same as expected. The authors interpret this as a kind of prediction error over sensory features, which is consistent with the idea that dopamine neurons encode surprising sensory signals—here, the flavor of the milk. These experiments nicely control the expectation of sensory stimulation while modulating information in a surprising way about the reward delivered. Such additional information may not be directly related to the value of what was ingested, but may be used as an informative signal that the context of the behavioral task may have changed.

Hikosaka and colleagues (Nakahara et al., 2004) have demonstrated the ability of dopamine neurons to track reward prediction errors about informative cues (Bromberg-Martin & Hikosaka, 2009), and also shown dopaminergic activity that is best explained by models that also account for contextual changes (Nakahara et al., 2004). Nakahara et al. (2004) used electrophysiological recordings of putative dopamine neurons in non-human primates, a classical conditioning task, a context-dependent conditioning task, and computer modeling to demonstrate that at least two classes of dopamine neurons could be identified: dopamine neurons that track classic temporal difference reward prediction errors and dopamine neurons that detect context-dependent reward prediction errors.

Bromberg-Martin and Hikosaka (2009) used a choice task to demonstrate that macaques preferentially choose options that lead to advance information about the magnitude of reward to be delivered at a later time. Not only did monkeys display this behavioral preference, but dopamine neurons that showed reward prediction error responses to reward delivery and predictive cues also showed responses that increased when predictive advanced information was provided.

Together, these experiments highlight a strong connection between dopamine neuron activity and surprising information and the importance of context. New information or surprising changes in the environment may have intrinsic value to a system that is geared towards learning statistical structure about appetitive pro-survival events. New information or a surprising change in the context of delivered signals would be important to alert to and may simultaneously be treated as potentially rewarding and potentially punishing. In this sense, one might expect to also see an aversive expectation error response signaled in parallel with what we are hypothesizing as a dopaminergic appetitive expectation error reported above. These responses would not necessarily be learned ones, but rather an intrinsic valuation response to any 'new information' or events experienced for the first time that could be unlearned should the subsequent associations be consistently positive or negative.

12.2.6 Dopaminergic Responses to Aversive Stimuli…?

The range of signals encoded above may generally be thought of as signals of positive valence, or at least not worse than neutral. However, there has been a significant amount of work demonstrating dopaminergic activity to aversive stimuli, including noxious electric shock (Guarraci & Kapp, 1999; Young, 2004; Brischoux et al., 2009; Zweifel et al., 2011; de Jong et al., 2019), tail pinch (Mantz et al., 1989; Zweifel et al., 2011), air puff to the eye (Matsumoto & Hikosaka, 2009) or face (Cohen et al., 2012), stress (Abercrombie et al., 1989; Anstrom & Woodward, 2005), and social defeat (Cao et al., 2010). Questions that remain in all investigations of dopamine neuron function include whether the characterized neurons are in fact dopamine neurons (Ungless & Grace, 2012). Further, it is unclear whether the experimental paradigms that demonstrate dopamine neuron activity to aversive stimuli control for alternative possibilities (Tanimoto et al., 2004). For instance, any of these apparent aversive events may not be interpreted as aversive, since many of the animals may not have had any experience with these kinds of stimulation prior to the initial work of the experimenter. Thus, any of these seemingly aversive stimuli could also be interpreted by the animal as simply 'novel' or 'potentially informative' in an otherwise highly controlled environment.

12.2.7 Summary and Discussion of Dopamine-Centric Limitations

Altogether, these studies demonstrate that dopaminergic encoding of temporal difference reward prediction errors is only part of the story. There is clear evidence that at least a subset of dopamine neurons encode temporal difference reward prediction errors (Montague et al., 1996; Watabe-Uchida et al., 2017). Dopamine release in human striatum also encodes reward prediction errors, but also appears to integrate this term with contextual information about counterfactual outcomes (Kishida et al., 2016; Moran et al., 2018). This latter point raises questions about the mechanisms that lead to dopaminergic encoding of counterfactual prediction errors—'are these signals a result of modulation of dopamine-releasing terminals that natively would otherwise encode standard reward prediction errors, or are these terminals silent while counterfactual prediction errors are signaled by a different subset of dopamine-releasing neurons that innervate the same region of tissue?'. Above, we described work from the animal literature that shows that dopamine neuron activity seems to encode contextual and informative signals, and possibly even aversive signals. It is not clear whether these studies controlled for the possibility that the stimuli used to represent "non-rewarding" signals do not have appetitive associations acquired previously (e.g., due to routine animal handling procedures) or intrinsically, in that the stimuli that we associate with being neutral or aversive may be interpreted very differently by experimental animals that experience life very differently from organisms in the wild.

Another major question that is not answered by most of the studies above is the degree to which temporal difference learning is or is not at play for these dopaminergic responses. Except for the studies that confirm that dopamine neurons encode temporal difference reward prediction errors, temporal difference reinforcement learning models are not tested nor can be tested given the design of the reported experiments. Based on the data and results reported in such studies, temporal difference reinforcement learning cannot be ruled out. It may be that the reported dopamine responses are encoding temporal difference reward prediction errors in each of these cases but the experiments are not designed in a modeling-friendly manner, or that the 'receptive field' of the dopamine neuron responses under investigation may be tuned to a different objective function.

The foundational work in attempting to build a computational hypothesis about the generation of affective dynamics from reinforcement learning algorithms by Xiang, Rutledge, and Eldar and colleagues (Xiang et al., 2013; Rutledge et al., 2014; Eldar & Niv, 2015) exposes the core role of reward prediction errors (presumably encoded by dopamine neuron activity) in dynamically modulating subjective feelings and mood. However, the models that link reward prediction errors to dynamic changes in happiness or mood do not provide an obvious mechanistic account for how these signals may be integrated in the brain, specifically in processes that lead to the generation of subjective feelings.

In the case of the subjective happiness model (Rutledge et al., 2014), the model demonstrates that recent expected value estimates and reward prediction errors are correlated with changes in subjective ratings. The non-linear model that they provide is descriptive in the relationship between the role of value estimates and prediction errors about these expected reward values. Notably, these model terms are shown to correspond to activity in regions of the brain known to track these signals (independent of their connection to subjective ratings), and the insula is demonstrated to become active during the introspective report. Xiang et al. also implicate the striatum, orbital frontal cortex and insula (Xiang et al., 2013). These findings are an important first step in connecting neural computations and subjective experience but do not yield a clear computational hypothesis about the neural mechanisms that implement the integration of these signals into a subjective experience. Likewise, Eldar and Niv's work (Eldar & Niv, 2015) clearly demonstrates the two-way interaction of immediately signaled reward prediction errors and a longer-term impact of mood-related computations and the impact of these interacting signals on subjective ratings. But, the models developed to account for these changes do not clearly indicate how the brain might encode such calculations.

We believe that the joint demonstrations that dopamine neurons encode temporal difference reward prediction errors and that humans and non-human model organisms use this signal to guide value guided behavior provides a solid foundation to build computational hypotheses about how the brain generates dynamically changing subjective experiences. However, to fully capitalize on this foundation, we must seek to explain disparate findings about potential alternative roles for dopamine neuron signals while building upon our current best theories about the connection between dopamine neuron signals and behavioral control (Montague et al., 1996; Schultz et al., 1997; Montague et al., 2004; Glimcher, 2011).

12.3 Extending Temporal Difference Reinforcement Learning as a Functional Motif That Underlies Affective Dynamics: Valence Partitioned Reinforcement Learning

Temporal difference reinforcement learning algorithms were conceived to answer the problem of how an agent might learn about the value of different states in order to choose states that maximize ‘reward’ (Sutton & Barto, 1998). The computer agents implementing these algorithms obviously do not experience subjective reward; rather, the calculations aim to maximize a quantitative value defined by the algorithms’ objective function (s). A major result in this line of research was temporal difference reinforcement learning, which provides an optimal way to learn from experience and generate optimal estimates of the value of different states, given the specified objective function. Thus, given good estimates of the expected ‘reward’ value, an agent can implement a policy to choose in a specified manner. It is intuitive to connect this objective function to reward since we psychologically associate reward with pleasure and generally seek to maximize this in our own subjective lives. However, the learning algorithm could also be applied to generate optimal estimates for other values that an organism (or agent) may need to track, such as the expected harm value or the expected cost of various acts. Given optimally derived estimates of what states lead to more harm (now and into the future), policies can be implemented to act to avoid these states. Likewise, a nervous system may need to track the expected ‘information’ value, which could then be used in policies aimed at building models or explore versus exploit tradeoff decisions (e.g., when there is ‘more than expected’ entropy in the environment a system may benefit from more exploration before exploiting based on its current estimates).

This line of thinking and theory-based proposals that hypothesize that the serotonergic system may act as an opponent signal to reward prediction errors signaled by dopamine (Daw et al., 2002; Dayan & Huys, 2008) led us to hypothesize that the temporal difference learning algorithm may be used by other systems in the brain. We remain agnostic as to which systems in the brain may provide these kinds of signals but note that other (non-reward responsive) dopamine neurons and the serotonin system are prime candidates. For now, we outline a simple extension of traditional temporal difference reinforcement learning (specifically Q-learning, Watkins, 1989; Watkins & Dayan, 1992) by which we partition valence into two independent dimensions: positive and negative (Montague et al., 2016).

12.3.1 Classic Reward Versus Valence-Partitioned Temporal Difference Reinforcement Learning

First, we describe the classic (unidimensional valence) approach to temporal difference Q-learning. Then we extend this approach by one step and partition the valence of inputs such that experienced appetitive and aversive outcomes are handled by independent systems before being integrated at the level of an overall value estimate. Again, the goal of Q-learning is to learn to act optimally (e.g., take actions in order to maximize reward) in uncertain environments based on past experience. Here, the *Quality* of an action (a) in a given state (s) is given by $Q(s, a)$ rather than simply the value of a sate (as implied in Eqs. 12.1–12.4) and is updated by the familiar temporal difference reward prediction error (δ_t):

$$Q\left(s_t, a_t\right) \leftarrow Q\left(s_t, a_t\right) + \alpha * \delta_t \tag{12.5}$$

α is again the learning rate that determines how quickly the agent updates its expected value for the state-action pair. The temporal difference reward prediction error in Q-learning can be calculated as follows:

$$\delta_t = \left\{ r\left(s_t, a_t\right) + \gamma * \max_{\tilde{a}} Q\left(s_{t+1}, \tilde{a}\right) \right\} - Q\left(s_t, a_t\right) \tag{12.6}$$

Again, this should look very familiar to Eq. 12.4 above—now, $r(s_t, a_t)$ is the reward collected at time t following the state-action pair that occurs at time t; γ is once again a discounting parameter that weights how forward looking the agent is. The value of the future state (s_{t+1}) depends on the available actions ($\tilde{a}$). Here, $\max_{\tilde{a}} Q\left(s_{t+1}, \tilde{a}\right)$ represents that value of future states when the agent chooses the action a out of all possible actions $\tilde{a}$ that maximizes the expected state-action value in the immediate future state s_{t+1}. Using these Q-value estimates, the agent will enact its choice policy. The softmax policy is one policy that allows agents to make choices that balance exploiting current Q-value estimates versus exploring alternative actions so that Q-value estimates can be improved through experience. The softmax equation looks like this:

$$P\left(s_t, a_t\right) = \frac{e^{Q\left(s_t, a_t\right)/\tau}}{\sum_i e^{Q\left(s_t, a_{t,i}\right)/\tau}} \tag{12.7}$$

Equation (12.7) represents a Boltzmann distribution that specifies the probability $P(s_t, a_t)$ that action a_t will be chosen in state s_t given the current estimates of $Q(s_t, a_i)$. $a_{t,\,i}$ represents each of the possible actions, indexed by i while in state s_t. τ is a 'temperature' parameter that parameterizes the exploration versus exploitation trade-off: higher temperature values increase the variability of choices (weighted by the expected value $Q(\bullet)$) while lower temperatures crystalize behavior such that actions with current maximum $Q(\bullet)$ estimates are always chosen.

To overcome limitations of the 'dopamine/TD-reward'-centric models, we extend the traditional unidimensional valent Q-learning framework by partitioning the 'reward' and 'valuation system' into valence-specific 'Positive' (appetitive) and 'Negative' (aversive) systems. In this way, each system can be thought of as having a kind of receptive field for only appetitive or aversive inputs, respectively. We call this approach "Valence Partitioned" such that each system independently computes TD prediction errors and updates separate Q-values for positive (P) and negative (N) value estimates:

$$Q^P\left(s_t,a_t\right) \leftarrow Q^P\left(s_t,a_t\right) + \alpha^P * \delta_t^P \tag{12.8}$$

$$Q^N\left(s_t,a_t\right) \leftarrow Q^N\left(s_t,a_t\right) + \alpha^N * \delta_t^N \tag{12.9}$$

These *"P"* and *"N"* systems independently track the positive quality ($Q^P(s_t, a_t)$) and the negative quality ($Q^N(s_t, a_t)$) of state-action pairs, respectively. The *P* and *N* system Q-values are updated according to their own independent learning rates (α^P, α^N, respectively). They are updated by temporal difference prediction errors as in unidimensional Q-learning but do so only for their respective valence-specific receptive fields.

For the positive-valence *P* system, the appetitively oriented TD prediction error (δ_t^P) takes the form:

$$\delta_t^P = \begin{cases} outcome_t + \gamma^P * \max\limits_a Q^P\left(s_{t+1},a\right) - Q^P\left(s_t,a_i\right) if\ outcome_t > 0, \\ 0 + \gamma^P * \max\limits_a Q^P\left(s_{t+1},a\right) - Q^P\left(s_t,a_t\right) if\ outcome_t \le 0 \end{cases} \tag{12.10}$$

where γ^P is the *P* system temporal discounting parameter directly analogous to the standard unidimensional Q-learning model temporal discounting parameter.

The negative-valence *N* system similarly encodes an aversively oriented TD prediction error term (δ_t^N):

$$\delta_t^N = \begin{cases} 0 + \gamma^N * \max\limits_a Q^N\left(s_{t+1},a\right) - Q^N\left(s_t,a_t\right) if\ outcome_t \ge 0, \\ outcome_t + \gamma^N * \max\limits_a Q^N\left(s_{t+1},a\right) - Q^N\left(s_t,a_t\right) if\ outcome_t < 0 \end{cases} \tag{12.11}$$

where γ^N is the *N* system temporal discounting parameter. Notably, the *P* system only tracks appetitive outcomes (Eq. 12.10, $outcome_t > 0$) and the *N* system only tracks aversive outcomes (Eq. 12.11, $outcome_t < 0$); otherwise, both systems ignore outcomes that are not within their receptive field (treats the opponent valence outcome as though nothing happened, Eqs. (12.10) and (12.11), $outcome_t \leq 0$ or $outcome_t \geq 0$, respectively).

Before the *P* and *N* systems' estimates of appetitive and aversive value can be used to direct action, they must be integrated in some manner such that a policy can use these estimates to direct choice. A simple approach is to contrast them (though other schemes are possible):

$$Q\left(s_t,a_t\right) \leftarrow Q^P\left(s_t,a_t\right) - Q^N\left(s_t,a_t\right) \tag{12.12}$$

Now the output of the integrated Q-value (Eq. 12.12) can be input in to the softmax policy equation (Eq. 12.6; or some other specified policy) and a decision about the best action can be made.

Temporal Difference Reinforcement Learning with valence partitioning serves three purposes here. One, as a hypothetical account for how a system that is an opponent, yet complementary, to dopaminergic reward prediction error signals might behave (Daw et al., 2002; Dayan & Huys, 2008; Montague et al., 2016). Two, to serve as a hypothesis to account for observed serotonergic signals in humans (Moran et al., 2018; Bang et al., 2020). And three, as a hypothetical example of how one might extend the concept of optimal control and explore the idea that temporal difference learning algorithms are a functional motif used by multiple systems in the nervous systems of organisms that express complex adaptive behavior and behavioral control. For example, one could extend this framework such that expectations about the frequency of common versus rare signals could be optimally tracked and signaled as an 'entropy' prediction error that would alert the system to novel or rare signals or surprising changes in context that ought to be attended to and investigated (or avoided depending on the agent's estimated value of new information).

Simultaneously recorded measurements of serotonin and dopamine release at sub-second temporal resolution in humans during decision-making is consistent with serotonin and dopamine acting as opponent signals (Kishida et al., 2016; Moran et al., 2018; Bang et al., 2020). In each of these reports, the measured serotonin responses are consistent with a temporal difference aversive prediction error signal and, in the case of Moran et al., 2018, are shown to anti-correlate with simultaneously measured dopamine prediction error signals that integrate reward prediction errors and counterfactual prediction errors (Kishida et al., 2016; Moran et al., 2018). Sub-second serotonin and dopamine fluctuations are also shown to anticipate actions of the participant, which may be interpreted as a signal related to behavioral control or a prediction error signal associated with anticipated outcomes—these are not necessarily mutually exclusive hypotheses.

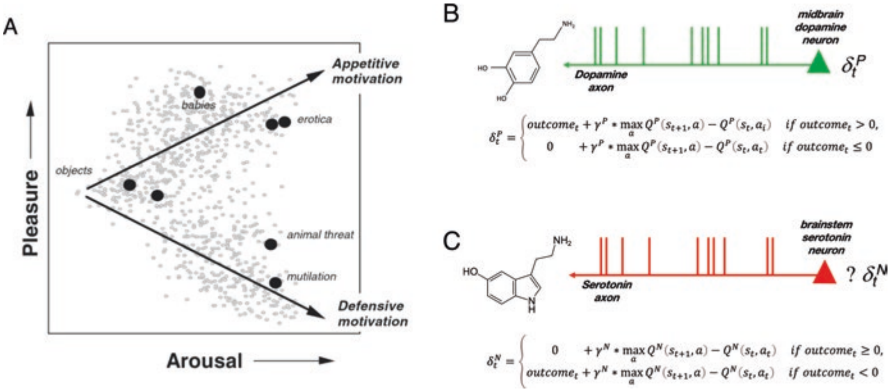


Fig. 12.3 Dynamic affect from valence partitioned reinforcement learning. (**a**) The international affective pictures system (IAPS) provides a widely utilized database of emotionally evocative images that have been rated by men and women for dimensions of pleasure and arousal (and dominance) (Lang & Bradley, 2007). (**b**) Valence Partitioned Reinforcement Learning (VP-RL) largely leaves dopamine neurons' relationship to positive valence (i.e., psychologically rewarding) stimuli intact; the main difference is that the inability of this system to track variable magnitude aversive outcomes is made explicit. (**c**) VP-RL posits that an additional independent system that runs in parallel but also uses TD-RL to track and estimate the expected value of aversive outcomes; we hypothesize that the serotonin system may act to track and signal aversive prediction errors (δ_t^N), but other neuromodulatory systems can be considered as alternative hypotheses. Positive system prediction errors (δ_t^P), hypothesized to be delivered by dopamine are well suited to drive appetitive motivational responses as cues (e.g., images) that are predictive of positive outcomes would elicit anticipated value driven prediction errors. In a similar manner, negative system prediction errors (δ_t^N) would be suited to drive defensive motivational responses. Interestingly, the independence of these systems in the VP-RL framework suggests that these signals can be integrated or contrasted by receptive systems that may in turn drive increases in arousal or enhance the discrimination of states and actions that result in complex valence superposition, respectively

Partitioning incoming appetitive (positive, P) and aversive (negative, N) signals would not be a challenge for biological systems and doing so would increase the dynamic range of the spectrum of valence interpretations. Behavioral results from human participants subjectively rating pictures for valence and arousal suggest that appetitive and aversive stimuli may not be unidimensional but rather independent dimensions that may be integrated in the behavioral report (Fig. 12.3, Lang et al. 2007). For example, separate P and N systems may send prediction error signals that are integrated downstream ($P + N$) or contrasted ($P - N$) depending on the neurotransmitters and receptors that carry and receive these signals, respectively (Montague et al., 2016). The neuroanatomy of the ascending valuation systems that include dopamine, serotonin, and norepinephrine neurons are prime candidates for this kind of diverse signaling (Fig. 12.4, Schiff & Plum, 2000; Doya, 2000).

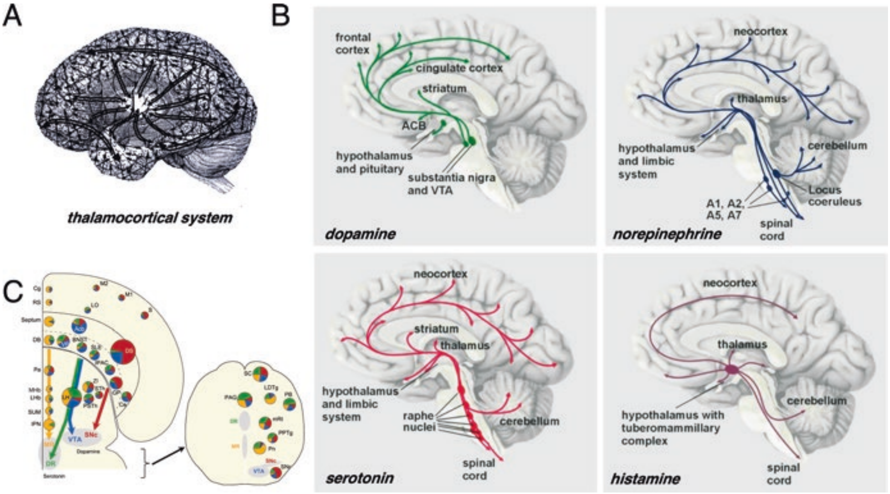


Fig. 12.4 *Dynamic Affective Core.* The original *dynamic core* hypothesis (Edelman & Tononi, 2000), similar to other neuroscientific theories of consciousness, is largely (**a**) corticothalamic centric. We propose the *dynamic affective core*, which explicitly incorporates the (**b**) ascending valuation systems (e.g., dopamine, serotonin, norepinephrine, and histamine)). Input from all over the brain is able to drive and modulate these systems wherein they provide critical neuromodulatory feedback. For example, (**c**) In the mouse, where detailed neuroanatomical tracing can be performed with the help of viral and sophisticated genetic tools, dopamine and serotonin neurons are observed to receive monosynaptic input from and send directly back signals to the amygdala, hypothalamus, thalamus, insula, cingulate cortex, striatum and many other cortical and subcortical structures (Ogawa et al., 2014). (**a**) Schematic of corticocortical and thalamocortical connections that comprise the core structures that dynamically encode and represent the contents and spatio-temporal context of conscious experience (images adapted from Edelman & Tononi, 2000). (**b**) Schematic of ascending projections of dopamine, serotonin, norepinephrine, and histamine neurons from the midbrain and brainstem (images adapted from Fuchs & Flügge, 2004). (**c**) Schematic of monosynaptic inputs to dopamine (ventral tegmental area, VTA and substantia pars compacta. SNc) and serotonin (median raphe, MR and dorsal raphe, DR) neurons in the mouse brain (images adapted from Ogawa et al., 2014). Neural structures that project to the dopamine and serotonin neurons in their respective nuclei are color coded according to their projection target. *VTA* blue; *SNc* red; *MR* yellow; and *DR* green. Pie charts indicate the proportion of neurons in that region that project to each of the respective nuclei

12.4 Subjective Experience and the 'Dynamic *Affective* Core' Hypothesis

"Subjective feelings" are at the core of what humans try to describe when we communicate our experience. The contents (i.e., objects and spatio-temporal context) of our experience are part of the description, but it is the subjective feeling bound to those elements that drive our descriptions. Fundamentally, these phenomenal experiences are integral to how we perceive, navigate, and communicate about the world and consist not only of the informative content of the environmental context we find ourselves in, but critically the subjective feelings associated with it. "How we feel" from moment to moment impacts our mood and behavior (and vice versa) and likely involves an extensive network of dynamically interacting neural structures. Edelman and Tononi proposed the *dynamic core* as a hypothesis about how neural activity may generate conscious experiences (Tononi & Edelman, 1998; Edelman & Tononi, 2000). The *dynamic core hypothesis*, as originally stated (Edelman & Tononi, 2000), has two fundamental parts:

1. "A group of neurons can contribute directly to conscious experience only if it is part of a distributed functional cluster that, through reentrant interactions in the thalamocortical system, achieves high integration in hundreds of milliseconds."
2. "To sustain conscious experience, it is essential that this functional cluster be highly differentiated, as indicated by high values of complexity."

In this hypothesis, cortical-cortical and thalamo-cortical loops are fundamental to the 'dynamic core'; timing is key, as is reverberant activity such that there is wide-spread activity (throughout the cortex) that is tightly coupled in a brief window of time. Further, not just any coupled activity will do: they propose a complexity metric that is aimed at identifying specific levels of information integration and differentiation. This notion has evolved into the Integrated Information Theory of consciousness with phi (Φ), a measure of *information integration*, central to the theory (Tononi et al., 2016 for a recent review). In the original formulation of the *dynamic core hypothesis,* the ascending valuation systems that include dopaminergic, serotonergic, norepinephrinergic, and cholinergic neurons (Schiff & Plum, 2000) is noted for their likely role in *dynamically modulating behavior* in response to "external stimuli, learning and memory, emotion, and cognition" and in coupling "value and emotions" to conscious experience (Edelman & Tononi, 2000). Within the framework of the dynamic core hypothesis, it seems that the role of the ascending valuation systems is simply to shape the cortical networks based on the organism's life experience (learning) and to drive behavioral dynamics *in response to* subjective emotional experience.

While we find the dynamic core hypothesis useful in depicting the notion of a momentary, widely distributed functional cluster of neural activity that is necessary for representing the contents of a conscious experience, we believe it lacks a critical component of subjective phenomenal experience—the emotional subjective affect that *colors* what would otherwise simply be a dry representation of integrated information collected by the sensory systems.

The original dynamic core hypothesis (Edelman & Tononi, 2000) does not include an account for the central role dopaminergic signals likely play in driving dynamic changes in subjective experience. Though the role dopamine neurons play in signaling reward prediction errors was demonstrated at the time (Montague et al., 1996; Edelman & Tononi, 2000), those findings were not discussed. Since then, the dynamic core hypothesis seems to have evolved into Integrated Information Theory where the main focus has been on developing a theoretic model that quantifies the structure of information integration that would support consciousness—whether it be biological or otherwise—and less emphasis has been placed on determining how any such a dynamic core may generate conscious experience.

12.4.1 The Dynamic Affective Core Hypothesis

We propose to update the *dynamic core* hypothesis to include the ascending valuation systems and suggest that emotional circuitry and ascending neuromodulatory systems are critical components of a dynamic affective core. We hypothesize that this dynamic affective core (Fig. 12.4) is necessary for human subjective experience. In contrast to the dynamic core hypothesis, we view the neuromodulatory systems (i.e., dopaminergic, serotoninergic, adrenergic, cholinergic, and histaminergic neurons) as a necessary component that was excluded from the original dynamic core description. Also, in contrast to the dynamic core, we hypothesize that emotional circuitry is a necessary element of the dynamic affective core that generates human subjective experience, and that together the emotional circuitry and ascending neuromodulatory systems engenders the dynamic core content with the "what it is like…" aspects of subjective feelings and qualitative conscious experience. We believe that to make progress in understanding the nature of the dynamic affective core and how it generates consciousness, computationally constrained hypotheses will be necessary and will include the foundational work connecting temporal difference learning algorithms to dopamine neurons and their cortical and subcortical targets.

12.4.2 Experimental Support for the Dynamic Affective Core Hypothesis

Much research has been done to elucidate neural structures that support neural representations of emotion-related behavior and subjective phenomenal experience (LeDoux, 2000; Lang & Bradley, 2010). These structures (e.g., amygdala, insula, striatum, and orbital frontal/ventromedial prefrontal cortex) and their dynamic interaction are hypothesized to be critical elements in a dynamic affective core that supports a dynamically evolving representation of continuously evolving emotional states that are in turn bound to dynamically evolving contextual sensory states. To determine the composition of these dynamic systems and their behavior in regard to affective dynamics, we turn again to computational approaches to human neuroscience.

Above, we reviewed recent research that connects reward prediction errors (putatively encoded by dopamine neuron activity) with dynamic changes in subjective feelings about social gestures (Xiang et al., 2013), subjective well-being (Rutledge et al., 2014) and mood (Eldar & Niv, 2015). It has also been shown that reward prediction errors are associated with sub-second fluctuations in dopamine release (Kishida et al., 2016; Moran et al., 2018) and aversive prediction errors are associated with sub-second serotonin release (Moran et al., 2018) in the striatum, both of which are consistent with the VPRL hypothesis described above. In both of these studies, dopamine and serotonin fluctuated in ways that were consistent with how participants' feelings ought to have been modulated given the reward prediction error and counterfactual error signals present in the game. All together, these results are consistent with the dynamic affective core hypothesis, though significant gaps remain. Direct dopamine and serotonin measurements with the temporal resolution required are currently restricted to the striatum, though technology appears to be on the horizon that may overcome this challenge and permit real-time neurochemical detection throughout the human brain (Montague & Kishida, 2018). Dopamine and serotonin (and norepinephrine) neurons project from the midbrain and brainstem throughout the human brain (Fig. 12.4), and whole-brain connections to the dopamine and serotonin neurons have been demonstrated (Watabe-Uchida et al., 2012; Ogawa et al., 2014). Thus, through direct and indirect pathways, dopamine neurons likely broadcast prediction error signals throughout the brain. Consistent with this idea, one ought to see evidence of reward prediction errors modulating whole networks, which would be consistent with dopamine neurons providing distributed parallel signals capable of shaping and also driving the synchronous activity of a dynamic affective core.

12.4.3 Reward Prediction Errors Modulate Task Specific Dynamic Cores

A few studies have begun to look for evidence that reward prediction errors modulate whole functional networks. These studies were performed investigating the role of reward prediction errors in instrumental reinforcement learning or associative learning tasks and did not probe associated subjective experiences. Nonetheless, these studies do demonstrate evidence that reward prediction errors modulate network-level dynamics consistent with task specific dynamic cores.

Using an associative learning task with BOLD imaging, den Ouden and colleagues demonstrated that prediction errors in the striatum modulate cortical coupling (den Ouden et al., 2010). In this task, participants were required to generate motor responses indicating whether an auditory tone (high or low) was followed by one of two visual stimuli (human faces or houses). The probability of each tone being followed by each visual stimulus was changed over time. Using a Bayesian learner model, expectations (i.e., probability that a visual stimulus would occur) were estimated throughout the task, and violations of those expectations generated prediction errors that parametrically modulated brain activity measured using fMRI. Visual stimulus non-specific prediction error signals were observed in the putamen and premotor cortex, whereas activity in the fusiform face area (FFA) was found to correlate with the probability of observing human face stimuli, and activity in the parahippocampal place area (PPA) correlated with the probability of observing houses. As such, responses in the FFA and PPA to faces and houses, respectively, appeared to be a function of how surprising each stimulus was, indicating that FFA and PPA regional activity is modulated by prediction errors over expectations of stimulus occurrence. Notably, nonlinear dynamic causal modeling was consistent with the hypothesis that prediction error signals in the putamen (a site of significant dopaminergic innervation) served to modulate functional connections from FFA and PPA to the dorsal premotor cortex. In all, these results demonstrated that regional activity in visual cortex is modulated by learning-relevant prediction error signals and that inter-regional functional connectivity within a visuomotor network (i.e., a task specific dynamic core) is modulated by prediction error signals emanating from human striatum. These findings are in line with a previous report (den Ouden et al., 2009) which used dynamic causal modeling to determine that learning-induced activity in visual cortex reflecting prediction error signals was mirrored by alterations in inter-regional functional connectivity between auditory and visual cortices, with auditory-to-visual top-down connectivity positively correlating with the prediction error-dependent regional activity in visual cortex.

BOLD activity in human striatum has also been shown to dynamically correlate with distributed brain regions in visual, motor, and prefrontal cortices in a manner consistent with orchestrating valence-processing mechanisms required for reinforcement learning (Gerrarty et al., 2018). In an fMRI-scanned instrumental conditioning task, participants learned which of two cues was paired with a visual stimulus. The pairings were associated probabilistically, and participants were given feedback (i.e., showing the words “correct” or “incorrect”) at the end of each trial. Choice behavior on this task was modeled such that reward prediction errors could be calculated during learning and these parametric responses could then be used to investigate changes in dynamic network connectivity using sophisticated computational tools for quantifying network dynamics (Medaglia et al., 2015). In particular, Gerrarty and colleagues were interested in investigating how a measure of “striatal flexibility” changes during reinforcement learning. Here, flexibility is a measure of dynamic network activity that indicates the degree to which a brain region functionally interacts with different brain networks over time (Bassett et al., 2011). The results demonstrated that striatal flexibility was associated with learning of cue-stimulus associations throughout the task, negatively correlated with model-derived individual-differences in learning rates, and positively correlated with individual choice temperature parameter values. Moreover, the increased striatal flexibility association with learning was determined to be implemented by increased functional coupling between nucleus accumbens and putamen with regions of visual cortex and by functional coupling between putamen and orbitofrontal and ventromedial prefrontal cortices. Together, these results suggest that regions that are highly innervated by dopaminergic inputs (e.g., nucleus accumbens, putamen, and orbitofrontal and ventromedial prefrontal cortices) are co-driven during instrumental tasks with positively- and negatively-valent feedback. This kind of dynamic network activity is consistent with our dynamic affective core hypothesis.

These studies demonstrate how the influence of putative dopaminergic reward prediction error signals may be investigated in non-invasive studies. However, direct measurement will be needed to determine whether these changes in network level representations are driven directly by dopaminergic fluctuations at key nodes or indirectly through the influence of nodes one or more synapses away within the dynamic affect core. These studies also did not investigate associated subjective experiences throughout these tasks, and future work will require experiments aimed at directly investigating the interaction of these network level dynamics and moment-to-moment changes in affect. One would expect, in these studies, that insula, amygdala, orbital frontal/ventromedial prefrontal cortex, and the striatum would be engaged as specific components of the dynamic affective core based on their previously demonstrated role in emotion and value-based decision-making behavior.

Other aspects of the dynamic affective core *hypothesis* that are not addressed in these studies is the relative lack in temporal precision and electrochemical specificity that constrains interpretation of BOLD imaging data. These studies clearly implicate regions of interest for further investigation, but BOLD imaging does not provide the temporal resolution required to observe the hypothesized affective core temporal dynamics of hundreds of milliseconds or less. Nor does fMRI provide the electrochemical specificity to discriminate the sources of neural activity that drive the blood-oxygen-level-dependent response (e.g., synaptic field potentials, somatic action potentials, or fast synaptic neurochemical signals). Studies utilizing MEG or intracranial measurements of human brain activity during conscious subjective experience may provide data with the requisite spatiotemporal resolution and, in the case of intracranial human electrochemical measurements (Montague & Kishida, 2018), the requisite neurochemical specificity to determine the necessary and sufficient components and behavior of the dynamic affective core.

12.5 Summary and Future Directions

Approaches using computational neuroscience to investigate *affective dynamics* are beginning to suggest methods that will enable objective investigations about the hardest problem in consciousness research. The subjective phenomenal experience of “what it is like…” to be human is not just about the contents (i.e., the objects and spatiotemporal context) of our experience. Rather, the subjective feelings or values that are also bound to these contents are what make qualitative phenomenal experience (i.e., qualia) unique to the experiencing individual. These values are likely learned (or at least modulated) through experience, become associated with states and actions that result from past states and actions, and become associated with states and actions that are predictive of future experiences as we move through space and time. Dynamic algorithms derived from artificial intelligence research (i.e., temporal difference reinforcement learning) that learn and change based on experience appear to be embodied by key neurobiological substrates and have begun to provide critical insight into how human nervous systems may encode subjective value. These models, in combination with computational approaches to characterize complex dynamic network structure, are beginning to permit the expression of quantitative hypotheses about the neural architecture that supports conscious subjective experience in humans. This, in turn, provides guidance regarding the kinds of experiments required for advances in consciousness and affective dynamics research.

We introduce the dynamic affective core hypothesis. It is different from the original 'dynamic core' hypothesis as stated by Edelman and Tononi (2000) and previous notions of a psychological affective core, which are not necessarily tied to the neural structure and dynamics that are central to the dynamic affective core that we describe. The dynamic affective core departs from the original notion of the *dynamic core* by specifically requiring the ascending valuation systems (i.e., dopaminergic, serotonergic, noradrenergic, and histaminergic neurons) and emotional circuitry (e.g., amygdala, insula, anterior cingulate cortex, and orbital frontal cortex) as necessary elements. The interaction of these systems is hypothesized to be fundamental to the binding of subjective feeling and affective value to the contents (i.e., objects and spatiotemporal context) represented in the cortico-thalamic systems of focus in the original dynamic core hypothesis. In this way, the dynamic affective core hypothesis may serve as a bridge connecting cognition, emotion, and the impact of 'surprises' on individuals emotional experience (Mellers et al., 2013). In the dynamic affective core hypothesis, we retain the notion of the functional cluster and timing aspects of the original dynamic core hypothesis; however, we posit that the role of the ascending valuation systems (like the distributed dopaminergic signal) is necessary for not only the selection of which functional clusters are active but also for creating and maintaining functional clusters that bind subjective value and emotion to the contents and context that activity in the cortico-thalamocortical networks encode. The timing of dopamine neuron activity (Fig. 12.1) and modulations in extracellular dopamine levels (Fig. 12.2) are consistent with the requisite timing to achieve "high integration in hundreds of milliseconds". Also, the anatomical projections of dopamine (and other ascending valuation systems) neurons (Fig. 12.4) make plausible parallel simultaneous signaling to cortical, thalamic, and subcortical structures which would allow adaptive formation of new functional clusters or dynamic modulation of existing ones. The dynamic affective core hypothesis is also significantly different from IIT (Tononi et al., 2016), which is primarily concerned with quantifying dynamic network structure (the amount of information integration and differentiation in a dynamic network) that might support conscious experience. The dynamic affective core is also distinct from a global workspace theory (Baars, 1997) or a global neuronal workspace as proposed by Dehaene and Naccache, 2001. Chiefly, like the dynamic core and the global neuronal workspace hypotheses, the dynamic affective core is grounded by neurobiological data; however, unlike the dynamic affective core hypothesis, both the dynamic core and the global neuronal workspace hypotheses appear to be extremely cortical-thalamocortical centric. Some of the functional attributes of the 'workspace neurons' in the global neuronal workspace appear consistent with the long range and diffuse projections of dopamine, serotonin, and norepinephrine neurons, but to our knowledge these neurons are not explicitly discussed as likely candidates (Dehaene and Naccache, 2001); further, dopamine, serotonin and norepinephrine neurons appear to have functional attributes that either go beyond the role of 'workspace neurons' to the point that they may be inconsistent with this notion. Our dynamic affective core hypothesis does not reject the critical role of cortical-thalamocortical networks and reentrant activity but adds the requirement that the dopaminergic system (and other valuation systems) be considered as critical components that coactivate, shape, and coordinate network activity underlying affective dynamics and associated subjective feelings.

The role (specifically) of the dopaminergic system in the dynamic affective core implies a role for temporal difference learning algorithms and dynamic modulation of the dynamic affective core though the delivery and representation of the computational signals described in this framework. We want to make explicit this connection in our hypothesis. The dynamic affective core hypothesis requires computational depictions of dynamic network structure in order to move the work forward. We propose a first step in extending the dynamic affective computational framework with our valence-partitioned reinforcement learning (VPRL) model. VPRL describes one way that the dynamic affective core may be modulated independently by positive and negative input, which are expected to be able to also occur independently in nature. VPRL prediction error signals about reward and punishment are consistent with simultaneously recorded sub-second data of dopamine and serotonin in humans (Kishida et al., 2016; Moran et al., 2018) and with the non-linear relationship of pleasure and arousal in consciously rated IAPS images (Fig. 12.3). The neurocomputational framework put forward in the dynamic affective core hypothesis may also be used to investigate the neurobiology underlying emotion behavior observed in reaction to ‘surprising’ information in real world settings (Mellers et al., 1997, 2013; Bhatia et al., 2019). At the behavioral level, errors in predicted outcomes seem to drive the strongest emotional reactions (Mellers et al., 1997; Villano et al., 2020). Other ideas that are likely to inform models about subjective experience and the neurobiological dynamics that support it are likely to come from research exploring the role of various reinforcement learning model elements like variations in model-based implementations or off-policy learning strategies (Doya, 2000; Montague et al., 2006, 2016; Bach & Dayan, 2017; Huys & Renz, 2017) and how they interact with dynamic functional networks. To the latter, we argue for the use of computational models and descriptions of network architecture (Bassett et al., 2011; Medaglia et al., 2015). As research connecting these areas emerges, we speculate the need for mathematically depicted network structures to describe the details of the structure and function of the dynamic affective core and its relationship to conscious subjective experience.

We focus much of our review on the neurobiology of dopaminergic signals and their connection to temporal difference reward prediction errors. These neurons and their impact on behavioral control and learning have a rich literature that is grounded on the initial discovery of Montague, Dayan, and Sejkowski (1996) that dopamine neurons encode temporal difference reward prediction errors. Other systems that are certainly involved in dynamic affective processing and consciousness include the serotonergic, noradrenergic, and cholinergic and histaminergic systems (Schiff & Plum, 2000). Attempts to model these other systems has yet to yield a clear picture, but current evidence strongly suggests a role for serotonin in aversive processing (Dayan & Huys, 2008; Cools et al., 2011; Rygula et al., 2015; Moran et al., 2018; Bang et al., 2020; Doya et al., 2021) and norepinephrine and cholinergic signals in arousal and attention (Schiff & Plum, 2000). Our valence-partitioned reinforcement learning model is consistent with dopamine and serotonin acting as opponent (orthogonal) systems that signal appetitive and aversive prediction errors, respectively and independently (also see Montague et al., 2016). Moran and colleagues observed that dopamine and serotonin release appear to encode these signals in the striatum simultaneously and in a colocalized manner in humans, which suggests that downstream dopamine and serotonin receptors may integrate or contrast these signals to give rise to a spectrum of neural interpretations. Notably, an integration of appetitive and aversive prediction errors is consistent with a saliency signal that may directly or indirectly engage arousal systems and direct attention towards relevant environmental features; contrasting these signals would increase the signal to noise in systems gauging whether to increase or decrease appetitive versus aversive representations (Montague et al., 2016). Clearly, more work is needed to elucidate what dopamine, serotonin, norepinephrine, acetylcholine, and histamine release encode in the human brain and what role these signals play in affecting the hypothesized dynamic affective core.

We hope it is apparent that we should no longer ignore the investigation of behavior directly associated with subjective human experience (i.e., self-report). Quantifying subjective experience is challenging. Combining questions like, “How much pain do you feel?” with a visual analogue scale *is* the gold standard for assessing pain in clinical settings and really the only way to directly capture how a person feels in the moment. What is good about the visual analogue scale (and related measures) is that it reliably assesses subjective feeling and is a semi-quantitative and reproducible choice behavior. The latter points allow researchers to integrate subjective self-report ratings with the computational models (e.g., reinforcement learning framework) and model the answers as value-based decisions dependent on states and available actions. This approach, in combination with computational depictions of network structure and dynamics, will allow the field to translate reports about subjective feelings into an empirical and mathematical framework capable of precise hypothesis testing (i.e., computational modeling) analogous to what several groups have begun to do (Xiang et al., 2013; Rutledge et al., 2014; Eldar & Niv, 2015).

We propose the dynamic affective core hypothesis to be tested within the domain of computational human neuroscience to tackle the ‘hard problem’ of consciousness. The ‘hard problem’ of consciousness originally stated by Chalmers (1996) has stood as a major barrier in scientific progress in consciousness research and the subjective aspect of affective dynamics. We take the position that prescientific descriptions of phenomena always appear as ‘hard problems’ given that the state of scientific knowledge at the time of such distinctions are not up to the task of making the problem appear ‘easy’ (Churchland, 2005). We are in a time where there is so much neuroscientific knowledge that it may seem inconceivable that there are natural neural phenomena yet to be unraveled, but human consciousness stands as a definitive example. Our challenge is to convert consciousness research from a philosophically hard problem as it seems to be to one that has some scientific traction. This can only be achieved if we tackle it as an ‘observable’ phenomenon even if such observations are initially reliant on simple behavioral reports. The way through will be to constrain our hypotheses with mathematical models that relate brain and behavior such that errors and assumptions can be clearly observed and corrected. We introduce the dynamic affective core hypothesis as an idea that can take us further down this path and look to an integration of the computational neuroscience of decision-making and network dynamics to lead the way forward.

Acknowledgements This work was supported by funding from the NIH. KTK was supported by the NIH-NIDA (R01-DA048096), NIH-NIMH (R01-MH121099), NIH-NINDS (R01-NS092701), and NIH-NCATS (KL2TR001421). PS was supported by NIH-NIDA (T32-DA041349 and F31-DA053174).

References

Abercrombie, E. D., Keefe, K. A., DiFrischia, D. S., & Zigmond, M. J. (1989). Differential effect of stress on in vivo dopamine release in striatum, nucleus accumbens, and medial frontal cortex. *Journal of Neurochemistry, 52*(5), 1655–1658.

Anstrom, K. K., & Woodward, D. J. (2005). Restraint increases dopaminergic burst firing in awake rats. *Neuropsychopharmacology, 30*(10), 1832–1840.

Bach, D. R., & Dayan, P. (2017). Algorithms for survival: A comparative perspective on emotions. *Nature Reviews Neuroscience, 18*(5), 311–319.

Baars, B. J. (1997). In the theatre of consciousness. Global workspace theory, a rigorous scientific theory of consciousness. *Journal of Consciousness Studies, 4*(4), 292–309.

Bang, D., Kishida, K. T., Lohrenz, T., White, J. P., Laxton, A. W., Tatter, S. B., et al. (2020). Sub-second dopamine and serotonin signaling in human striatum during perceptual decision-making. *Neuron, 108*(5), 999–1010.

Bassett, D. S., Wymbs, N. F., Porter, M. A., Mucha, P. J., Carlson, J. M., & Grafton, S. T. (2011). Dynamic reconfiguration of human brain networks during learning. *Proceedings of the National Academy of Sciences, 108*(18), 7641–7646.

Bayer, H. M., & Glimcher, P. W. (2005). Midbrain dopamine neurons encode a quantitative reward prediction error signal. *Neuron, 47*(1), 129–141.

Beier, K. T., Steinberg, E. E., DeLoach, K. E., Xie, S., Miyamichi, K., Schwarz, L., et al. (2015). Circuit architecture of VTA dopamine neurons revealed by systematic input-output mapping. *Cell, 162*(3), 622–634.

Bhatia, S., Mellers, B., & Walasek, L. (2019). Affective responses to uncertain real-world outcomes: Sentiment change on Twitter. *PLoS One, 14*(2), e0212489.

Brischoux, F., Chakraborty, S., Brierley, D. I., & Ungless, M. A. (2009). Phasic excitation of dopamine neurons in ventral VTA by noxious stimuli. *Proceedings of the National Academy of Sciences, 106*(12), 4894–4899.

Bromberg-Martin, E. S., & Hikosaka, O. (2009). Midbrain dopamine neurons signal preference for advance information about upcoming rewards. *Neuron, 63*(1), 119–126.

Bromberg-Martin, E. S., Matsumoto, M., & Hikosaka, O. (2010). Dopamine in motivational control: Rewarding, aversive, and alerting. *Neuron, 68*(5), 815–834.

Camerer, C. F. (2003). *Behavioral game theory: Experiments in strategic interaction*. Princeton university press.

Cao, J. L., Covington, H. E., Friedman, A. K., Wilkinson, M. B., Walsh, J. J., Cooper, D. C., et al. (2010). Mesolimbic dopamine neurons in the brain reward circuit mediate susceptibility to social defeat and antidepressant action. *Journal of Neuroscience, 30*(49), 16453–16458.

Chalmers, D. J. (1996). *The conscious mind: In search of a fundamental theory*. Oxford university press.

Cho, J. R., Treweek, J. B., Robinson, J. E., Xiao, C., Bremner, L. R., Greenbaum, A., & Gradinaru, V. (2017). Dorsal raphe dopamine neurons modulate arousal and promote wakefulness by salient stimuli. *Neuron, 94*(6), 1205–1219.

Churchland, P. S. (2005). A neurophilosophical slant on consciousness research. *Progress in Brain Research, 149*, 285–293.

Churchland, P. S., & Churchland, P. M. (2002). Neural worlds and real worlds. *Nature Reviews Neuroscience, 3*(11), 903–907.

Cohen, J. Y., Haesler, S., Vong, L., Lowell, B. B., & Uchida, N. (2012). Neuron-type-specific signals for reward and punishment in the ventral tegmental area. *Nature, 482*(7383), 85–88.

Colombo, M. (2014). Deep and beautiful, The reward prediction error hypothesis of dopamine. *Studies in history and Philosophy of Science Part C: Studies in History and Philosophy of Biological and Biomedical Sciences, 45*, 57–67.

Crick, F., & Koch, C. (2003). A framework for consciousness. *Nature Neuroscience, 6*(2), 119–126.

Cunningham, W. A., Dunfield, K. A., & Stillman, P. E. (2013). Emotional states from affective dynamics. *Emotion Review, 5*(4), 344–355.

Clark, J. J., et al. (2010). Chronic microsensors for longitudinal, subsecond dopamine detection in behaving animals. *Nature Methods, 7*, 126–129.

Cools, R., Nakamura, K., and Daw, N. D. (2011). Serotonin and dopamine: unifying affective, activational, and decision functions. *Neuropsychopharmacology, 36*, 98–113.

Daw, N. D., Kakade, S., & Dayan, P. (2002). Opponent interactions between serotonin and dopamine. *Neural Networks, 15*(4–6), 603–616.

Dayan, P., & Niv, Y. (2008). Reinforcement learning: the good, the bad, and the ugly. *Current Opinion in Neurobiology, 18*(2), 185–96.

Dayan, P., & Huys, Q. J. (2008). Serotonin, inhibition, and negative mood. *PLoS Computational Biology, 4*(2), e4.

de Jong, J. W., Afjei, S. A., Dorocic, I. P., Peck, J. R., Liu, C., Kim, C. K., et al. (2019). A neural circuit mechanism for encoding aversive stimuli in the mesolimbic dopamine system. *Neuron, 101*(1), 133–151.

den Ouden, H. E., Daunizeau, J., Roiser, J., Friston, K. J., & Stephan, K. E. (2010). Striatal prediction error modulates cortical coupling. *Journal of Neuroscience, 30*(9), 3210–3219.

Den Ouden, H. E., Friston, K. J., Daw, N. D., McIntosh, A. R., & Stephan, K. E. (2009). A dual role for prediction error in associative learning. *Cerebral Cortex, 19*(5), 1175–1185.

Doya, K. (2000). Metalearning, neuromodulation, and emotion. In: Proc. Conf. Affect. Minds (Vol. 46, p. 47).

Doya, K. (2002). Metalearning and neuromodulation. *Neural Networks, 15*(4–6), 495–506.

Doya, K., Miyazaki, K. W., & Miyazaki, K. (2021). Serotonergic modulation of cognitive computations. *Current Opinion in Behavioral Sciences, 38*, 116–123.

Dehaene, S., & Naccache, L. (2001). Towards a cognitive neuroscience of consciousness: basic evidence and a workspace framework. *Cognition, 79*(1-2), 1–37.

Eban-Rothschild, A., Rothschild, G., Giardino, W. J., Jones, J. R., & de Lecea, L. (2016). VTA dopaminergic neurons regulate ethologically relevant sleep-wake behaviors. *Nature Neuroscience, 19*, 1356–1366.

Edelman, G. M., & Tononi, G. (2000). *A universe of consciousness: How matter becomes imagination*. Basic books.

Eldar, E., & Niv, Y. (2015). Interaction between emotional state and learning underlies mood instability. *Nature Communications, 6*(1), 1–10.

Eldar, E., Rutledge, R. B., Dolan, R. J., & Niv, Y. (2016). Mood as representation of momentum. *Trends in Cognitive Sciences, 20*(1), 15–24.

Etkin, A., Büchel, C., & Gross, J. J. (2015). The neural bases of emotion regulation. *Nature Reviews Neuroscience, 16*(11), 693–700.

Fehr, E., & Gächter, S. (2002). Altruistic punishment in humans. *Nature, 415*(6868), 137–140.

Forbes, N., & Mahon, B. (2014). *Faraday, Maxwell, and the electromagnetic field: How two men revolutionized physics*. Prometheus Books.

Fuchs, E., & Flügge, G. (2004). Cellular consequences of stress and depression. *Dialogues in Clinical Neuroscience, 6*(2), 171.

Fiorillo, C.D., Tobler, P.N., & Schultz, W. (2003). Discrete coding of reward probability and uncertainty by dopamine neurons. *Science, 299*(5614), 1898–1902.

Gantz, S. C., Ford, C. P., Morikawa, H., & Williams, J. T. (2018). The evolving understanding of dopamine neurons in the substantia nigra and ventral tegmental area. *Annual Review of Physiology, 80*, 219–241.

Gerrarty, R. T., Davidow, J. Y., Foerde, K., Galvan, A., Bassett, D. S., & Shohamy, D. (2018). Dynamic flexibility in striatal-cortical circuits supports reinforcement learning. *Journal of Neuroscience, 38*(10), 2442–2453.

Glimcher, P. W. (2011). Understanding dopamine and reinforcement learning: The dopamine reward prediction error hypothesis. *Proceedings of the National Academy of Sciences, 108*(Supplement 3), 15647–15654.

Guarraci, F. A., & Kapp, B. S. (1999). An electrophysiological characterization of ventral tegmental area dopaminergic neurons during differential pavlovian fear conditioning in the awake rabbit. *Behavioural Brain Research, 99*(2), 169–179.

Horvitz, J. C. (2002). Dopamine gating of glutamatergic sensorimotor and incentive motivational input signals to the striatum. *Behavioural Brain Research, 137*(1–2), 65–74.

Huys, Q. J., & Renz, D. (2017). A formal valuation framework for emotions and their control. *Biological Psychiatry, 82*(6), 413–420.

Hart, A. S., Rutledge, R. B., Glimcher, P. W., and Phillips, P. E. M. (2014). Phasic dopamine release in the rat nucleus accumbens symmetrically encodes a reward prediction error term. *Journal of Neuroscience, 34*(3), 698–704.

Horvitz, J. C., Stewart, T., & Jacobs, B. L. (1997). Burst activity of ventral tegmental dopamine neurons is elicited by sensory stimuli in the awake cat. *Brain Research, 759*(2), 251–258.

Kishida, K. T., Saez, I., Lohrenz, T., Witcher, M. R., Laxton, A. W., Tatter, S. B., et al. (2016). Subsecond dopamine fluctuations in human striatum encode superposed error signals about actual and counterfactual reward. *Proceedings of the National Academy of Sciences, 113*(1), 200–205.

Kishida, K. T., Sandberg, S. G., Lohrenz, T., Comair, Y. G., Sáez, I., Phillips, P. E., & Montague, P. R. (2011). Sub-second dopamine detection in human striatum. *PLoS One, 6*(8), e23291.

Kringelbach, M. L., & Berridge, K. C. (2017). The affective core of emotion: Linking pleasure, subjective well-being, and optimal metastability in the brain. *Emotion Review, 9*(3), 191–199.

Katahira, K., Matsuda, Y.-T., Fujimura, T., Ueno, K., Asamizuya, T., Suzuki, C., Cheng, K., Okanoya, K., & Okada, M. (2015). Neural basis of decision making guided by emotional outcomes. *Journal of Neurophysiology, 113*, 3056–3068.

Lammel, S., Lim, B. K., & Malenka, R. C. (2014). Reward and aversion in a heterogeneous midbrain dopamine system. *Neuropharmacology, 76*, 351–359.

Lang, P., & Bradley, M. M. (2007). The International Affective Picture System (IAPS) in the study of emotion and attention. *Handbook of Emotion Elicitation and Assessment, 29*, 70–73.

Lang, P. J., & Bradley, M. M. (2010). Emotion and the motivational brain. *Biological Psychology, 84*(3), 437–450.

LeDoux, J. E. (2000). Emotion circuits in the brain. *Annual Review of Neuroscience, 23*(1), 155–184.

Lerner, T. N., Shilyansky, C., Davidson, T. J., Evans, K. E., Beier, K. T., Zalocusky, K. A., et al. (2015). Intact-brain analyses reveal distinct information carried by SNc dopamine subcircuits. *Cell, 162*(3), 635–647.

Ljungberg, T., Apicella, P., & Schultz, W. (1992). Responses of monkey dopamine neurons during learning of behavioral reactions. *Journal of Neurophysiology, 67*(1), 145–163.

Lu, J., Jhou, T. C., & Saper, C. B. (2006). Identification of wake-active dopaminergic neurons in the ventral periaqueductal gray matter. *The Journal of Neuroscience, 26*, 193–202.

Mantz, J., Thierry, A. M., & Glowinski, J. (1989). Effect of noxious tail pinch on the discharge rate of mesocortical and mesolimbic dopamine neurons: Selective activation of the mesocortical system. *Brain Research, 476*(2), 377–381.

Matsumoto, M., & Hikosaka, O. (2009). Two types of dopamine neuron distinctly convey positive and negative motivational signals. *Nature, 459*(7248), 837–841.

Medaglia, J. D., Lynall, M. E., & Bassett, D. S. (2015). Cognitive network neuroscience. *Journal of Cognitive Neuroscience, 27*(8), 1471–1491.

Mellers, B., Fincher, K., Drummond, C., & Bigony, M. (2013). Surprise: A belief or an emotion? *Progress in Brain Research, 202*, 3–19.

Mellers, B. A., Schwartz, A., Ho, K., & Ritov, I. (1997). Decision affect theory: Emotional reactions to the outcomes of risky options. *Psychological Science, 8*(6), 423–429.

Menegas, W., Babayan, B. M., Uchida, N., & Watabe-Uchida, M. (2017). Opposite initialization to novel cues in dopamine signaling in ventral and posterior striatum in mice. *eLife, 6*, e21886.

Minsky, M. L. (1967). *Computation*. Prentice-Hall.

Montague, P. R., Hyman, S. E., & Cohen, J. D. (2004). Computational roles for dopamine in behavioural control. *Nature, 431*(7010), 760–767.

Montague, P. R., King-Casas, B., & Cohen, J. D. (2006). Imaging valuation models in human choice. *Annual Review of Neuroscience, 29*, 417–448.

Montague, P. R., & Kishida, K. T. (2018). Computational underpinnings of neuromodulation in humans. In *Cold Spring Harbor symposia on quantitative biology* (Vol. 83, pp. 71–82). Cold Spring Harbor Laboratory Press.

Montague, P. R., Kishida, K. T., Moran, R. J., & Lohrenz, T. M. (2016). An efficiency framework for valence processing systems inspired by soft cross-wiring. *Current Opinion in Behavioral Sciences, 11*, 121–129.

Montague, R. (2006). *Why choose this book?: How we make decisions*. EP Dutton.

Moran, R. J., Kishida, K. T., Lohrenz, T., Saez, I., Laxton, A. W., Witcher, M. R., et al. (2018). The protective action encoding of serotonin transients in the human brain. *Neuropsychopharmacology, 43*(6), 1425–1435.

Moerland, T.M., Broekens, J., & Jonker, C. M. (2018). Emotion in reinforcement learning agents and robots: a survey. *Machine Learning, 107*, 443–480.

Montague, P. R., Dayan, P., & Sejnowski, T. J. (1996). A framework for mesencephalic dopamine system based on predictive Hebbian learning. *Journal of Neuroscience, 16*(5), 1936–1947.

Nagel, T. (1974). What is it like to be a bat? *The Philosophical Review, 83*(4), 435–450. https://doi.org/10.2307/2183914

Nakahara, H., Itoh, H., Kawagoe, R., Takikawa, Y., & Hikosaka, O. (2004). Dopamine neurons can represent context-dependent prediction error. *Neuron, 41*(2), 269–280.

Ogawa, S. K., Cohen, J. Y., Hwang, D., Uchida, N., & Watabe-Uchida, M. (2014). Organization of monosynaptic inputs to the serotonin and dopamine neuromodulatory systems. *Cell Reports, 8*(4), 1105–1118.

Pagnoni, G., Zink, C. F., Montague, P. R., & Berns, G. S. (2002). Activity in human ventral striatum locked to errors of reward prediction. *Nature Neuroscience, 5*(2), 97–98.

Rutledge, R. B., Skandali, N., Dayan, P., & Dolan, R. J. (2014). A computational and neural model of momentary subjective well-being. *Proceedings of the National Academy of Sciences, 111*(33), 12252–12257.

Rygula, R., Clarke, H. F., Cardinal, R. N., Cockcroft, G. J., Xia, J., Dalley, J. W., et al. (2015). Role of central serotonin in anticipation of rewarding and punishing outcomes: Effects of selective amygdala or orbitofrontal 5-HT depletion. *Cerebral Cortex, 25*(9), 3064–3076.

Schiff, N. D., & Plum, F. (2000). The role of arousal and "gating" systems in the neurology of impaired consciousness. *Journal of Clinical Neurophysiology, 17*(5), 438–452.

Steinfels, G. F., Heym, J., Strecker, R. E., & Jacobs, B. L. (1983). Response of dopaminergic neurons in cat to auditory stimuli presented across the sleep-waking cycle. *Brain Research, 277*(1), 150–154.

Strecker, R. E., & Jacobs, B. L. (1985). Substantia nigra dopaminergic unit activity in behaving cats: Effect of arousal on spontaneous discharge and sensory evoked activity. *Brain Research, 361*(1–2), 339–350.

Sutton, A., & Barto, A. (2018). *Reinforcement learning* (2nd ed.). MIT Press.

Sutton, R. S., & Barto, A. G. (1998). *Introduction to reinforcement learning* (Vol. 135). MIT press.

Schultz, W., Dayan, P., & Montague, P. R. (1997). A neural substrate for prediction and reward. *Science, 275*(5306), 1593–1599.

Takahashi, Y. K., Batchelor, H. M., Liu, B., Khanna, A., Morales, M., & Schoenbaum, G. (2017). Dopamine neurons respond to errors in the prediction of sensory features of expected rewards. *Neuron, 95*(6), 1395–1405.

Takikawa, Y., Kawagoe, R., & Hikosaka, O. (2004). A possible role of midbrain dopamine neurons in short-and long-term adaptation of saccades to position-reward mapping. *Journal of Neurophysiology, 92*(4), 2520–2529.

Tanimoto, H., Heisenberg, M., & Gerber, B. (2004). Experimental psychology: Event timing turns punishment to reward. *Nature, 430*, 983.

Taylor, N. E., Van Dort, C. J., Kenny, J. D., Pei, J., Guidera, J. A., Vlasov, K. Y., Lee, J. T., Boyden, E. S., Brown, E. N., & Solt, K. (2016). Optogenetic activation of dopamine neurons in the ventral tegmental area induces reanimation from general anesthesia. *Proceedings of the National Academy of Sciences, 113*, 12826–12831.

Tononi, G., Boly, M., Massimini, M., & Koch, C. (2016). Integrated information theory: From consciousness to its physical substrate. *Nature Reviews Neuroscience, 17*(7), 450–461.

Tononi, G., & Edelman, G. M. (1998). Consciousness and complexity. *Science, 282*(5395), 1846–1851.

Ungless, M. A., & Grace, A. A. (2012). Are you or aren't you? Challenges associated with physiologically identifying dopamine neurons. *Trends in Neurosciences, 35*(7), 422–430.

Villano, W. J., Otto, A. R., Ezie, C. E., Gillis, R., & Heller, A. S. (2020). Temporal dynamics of real-world emotion are more strongly linked to prediction error than outcome. *Journal of Experimental Psychology: General, 149*(9), 1755–1766.

Watabe-Uchida, M., Eshel, N., & Uchida, N. (2017). Neural circuitry of reward prediction error. *Annual Review of Neuroscience, 40*, 373–394.

Watabe-Uchida, M., Zhu, L., Ogawa, S. K., Vamanrao, A., & Uchida, N. (2012). Whole-brain mapping of direct inputs to midbrain dopamine neurons. *Neuron, 74*(5), 858–873.

Watkins, C. J., & Dayan, P. (1992). Q-learning. *Machine Learning, 8*(3–4), 279–292.

Watkins, C. J. C. H. (1989). Learning from delayed rewards. PhD thesis, University of Cambridge, Cambridge, England.

Xiang, T., Lohrenz, T., & Montague, P. R. (2013). Computational substrates of norms and their violations during social exchange. *Journal of Neuroscience, 33*(3), 1099–1108.

Young, A. M. (2004). Increased extracellular dopamine in nucleus accumbens in response to unconditioned and conditioned aversive stimuli: Studies using 1 min microdialysis in rats. *Journal of Neuroscience Methods, 138*(1–2), 57–63.

Zaghloul, K. A., Blanco, J. A., Weidemann, C. T., McGill, K., Jaggi, J. L., Baltuch, G. H., & Kahana, M. J. (2009). Human substantia nigra neurons encode unexpected financial rewards. *Science, 333*(5920), 1496–1499.

Zweifel, L. S., Fadok, J. P., Argilli, E., Garelick, M. G., Jones, G. L., Dickerson, T. M., et al. (2011). Activation of dopamine neurons is critical for aversive conditioning and prevention of generalized anxiety. *Nature Neuroscience, 14*(5), 620–626.

Index

C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0